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Crises are conventionally considered times when low-productivity firms are driven out of the market at a higher rate so that resources are reallocated to more productive uses. However, economic growth has been unusually anaemic in the aftermath of the Great Recession (2008-2013). In this study, we look at the reduced efficiency of the resource reallocation process, highlighting the role of financial constraints. Credit restrictions hamper the development of potentially superior projects by both incumbents and new firms, a process that generates a misallocation of resources.
This study shows that deep recessions are primarily periods of counterproductive destruction rather than creative destruction, thus hampering economic growth and recovery. By expanding and widening the knowledge about the Great Recession and its aftermath, we also sought to contribute to better understand the foreseeable effects of the COVID-19 crisis.

Financial Constraints and Business Dynamics

Lessons from the 2008-2013 Recession

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Foreword

This study was assigned by the Francisco Manuel dos Santos Foundation to the University of Coimbra. The responsibility for the information and views set out in the study lies entirely with the authors and does not, in any way, reflect the views of the entities mentioned below.

This study uses data from the secured access version of the Integrated Business Accounts System (SCIE), supplied by the National Institute of Statistics (INE).

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Chapter 1
Introduction

Towards a new deep downturn, the COVID-19 crisis, the questions written by Paul Gauguin in what is perhaps his best-known painting, "Where do we come from? What are we? Where are we going?", become more relevant than ever. By expanding and widening the knowledge about the Great Recession caused by the 2008 financial crisis and its aftermath, we aim to improve the understanding of the likely effects of the COVID-19 crisis, while also provide tools that will hopefully be useful for policy making purposes in the new environment.

Crises are conventionally considered times when low-productivity firms are driven out of the market at a higher rate so that resources are reallocated to more productive uses. However, what if not every cloud has a silver lining? In fact, in the aftermath of the Great Recession, economic growth has been unusually anaemic in most advanced economies. The Great Recession seems to be different than previous ones, in the sense that output losses appear to be deeper and longer-lasting (Reinhart and Rogoff, 2014). Although researchers have documented several cyclical and structural channels through which a weakened financial system spills over unfavourably into the economy, our main original contribution in this study is to highlight the reduced efficiency of the observed resource reallocation process, with a particular focus on the role of financial restrictions.

Economic theory offers conflicting predictions on how a demand downturn and strict financial constraints affect firm behaviour. The Schumpeterian theory of creative destruction claims that recessions are times of "cleansing" when outdated or relatively unprofitable techniques and products are more prone to be driven out of the market so that productivity-enhancing reallocation becomes countercyclical (Caballero and Hammour, 1994). However, it can be the case that the cleansing effect is mitigated or even reversed by forces that weaken market selection, such as financial or labour market frictions (Barlevy, 2002, 2003; Caballero and Hammour, 2005; Ouyang, 2009).

Although there are diverse channels through which financial frictions affect firm performance and aggregate productivity, credit constraints and bank forbearance have been identified as the most relevant ones. In particular, Barlevy (2002) and Ouyang (2009) suggest that credit constraints hamper the development of potentially superior projects by incumbents and new firms, while an indirect effect via reduction of the competitive pressure on incumbent firms is also likely (Aghion et al., 2009).

In order to avoid reporting nonperforming loans, banks have also often followed a policy of forbearance with their problematic borrowers, engaging in sham loan restructurings that keep credit flowing to otherwise insolvent borrowers (Peek and Rosengren 2005; Caballero et al. 2008). By allowing the survival of underperforming businesses, aggregate productivity is harmed not only directly, but also through the negative impact that these companies generate on entry, growth, and exit flows (Caballero et al., 2008).

1.1. Study objectives

This study examines the impact of the Great Recession on the process of creative destruction and, in particular, the role of financial market frictions in resource allocation efficiency. We use Portuguese firm-level manufacturing and services census data from 2004 to 2017 to evaluate whether financially constrained firms were more exposed to credit market restrictions during the recession, regardless of their level of productivity. The working hypothesis is that during financial crises resource allocation is mostly driven by financial constraints rather than by productivity per se, a process that generates a misallocation of resources within existing firms and insufficient creative destruction (Peek and Rosengren, 2005; Giroud and Mueller, 2017). Since the best projects are deemed to require a higher level of R&D investment (and are also less able to generate collateral to borrow money), there will be a tendency towards funding less productive and less financially demanding projects in credit-constrained times (Barlevy, 2003; Paunov, 2012). Banks are also tempted to forbear bad debtors, by delaying the process of firm death to protect their balance sheets, thereby hindering a key mechanism of productivity growth.

Our analysis starts with the description of the Portuguese business dynamics before, during, and after the Great Recession. We will examine the impact of the crisis on resource reallocation and the allocative process itself. We will pay special attention to financial constraints as a key determinant of firm exit and growth, testing, in particular, the following subset of hypotheses:

1) Low-productivity firms are more likely to shrink/exit than equally financially constrained but highly productive firms.
2) The positive relationship between productivity and firms' growth/survival was weakened in the recession.
3) Financially constrained firms are more likely to shrink/exit than equally productive but unconstrained firms.
4) The negative relationship between financial constraints and firms' growth/survival was strengthened in the recession.
5) High-productivity firms shrank/exited during the recession, while less productive firms, but not financially constrained, grew and survived.

In a second step of our analysis, we will examine the phenomenon of zombie firms in Portugal. Zombie firms are a prime example of resource misallocation. Specifically, we will analyse the incidence of zombies, as well as the determinants of their transition into recovery and exit:

6) Zombie firms were less productive than non-zombies.
7) Resources sunk in zombie firms increased during the recession.
8) Restructuring increased the chances of recovery of zombie firms.

Barriers to exit and restructuring are also associated with resource misallocation. In 2012, two major reforms were implemented in the Portuguese insolvency regime: firstly, a hybrid pre-insolvency mechanism intended to promote businesses' reorganisation; and secondly, an out-of-court restructuring mechanism focused mainly on SMEs. Using the sample of financially distressed companies, we will examine whether the legislative changes enhanced the required resource reallocation effectively. We will test, in particular, the following subset of hypotheses:

9) The 2012 reform of the insolvency regime reduced the resources sunk in zombie firms.

10) The adverse impact of zombie firms on productivity-enhancing resource reallocation decreased with the 2012 reform.

Finally, aggregate productivity growth requires a continuous productivity-enhancing reallocation process. Therefore, we will decompose productivity growth to analyse the effects of entry, exit, and reallocation among existing firms during and after the crisis. In particular, we will test whether:

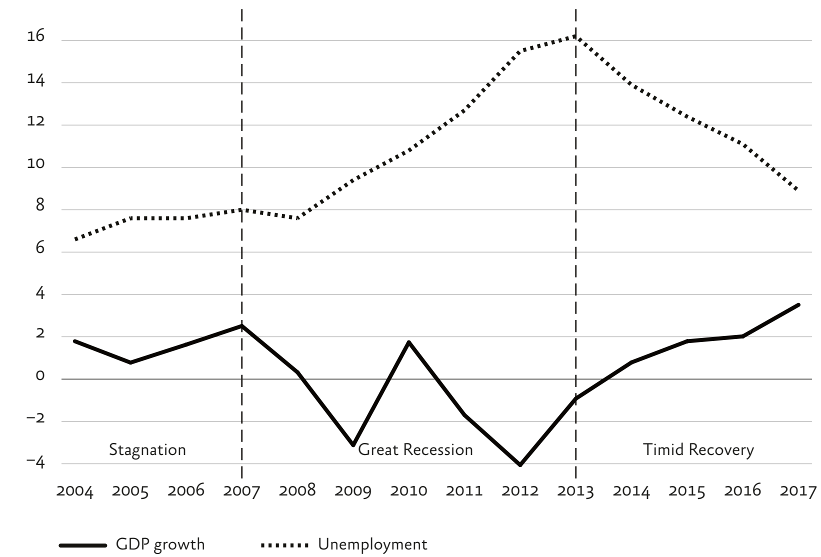
11) Changes in intra-firm productivity had a lower contribution to productivity growth during the recession.
12) Productivity-enhancing reallocation increased during the recession.
13) Severe recessions are times of counterproductive destruction, resulting from declining market shares and the exit of highly productive/financially constrained firms.

The Great Recession has allowed us to differentiate two distinct periods: the one before and the one after the crisis. At the start of the new millennium, the Portuguese economic boom in the mid-1990s became very sluggish, with the real gross domestic product (GDP) increasing by 1.2% per year (annual average between 2001 and 2007). By 2007 the unemployment rate was 8%, as shown in Figure 1.1. In a nutshell, this was the context in which the global financial crisis of 2008–2009 landed in the Portuguese economy, with the sovereign debt crisis of 2010–2012 following suit.

The impact was indeed catastrophic: between 2008 and 2013, the average annual growth rate of real GDP was a negative 1.3% (per year) peaking at −4.1% in 2012, following the austerity measures set out by the 2011 IMF-ECB-EU Memorandum of Understanding. The recession also triggered a dramatic increase in the unemployment rate, which more than doubled its pre-crisis levels, with a rise of 8.6 percentage points by 2013.

Inopportunely, the recovery was also mild. Although the real GDP growth rate became positive in 2014 it remained small, reaching a rate above the 2% only in 2017. Unemployment, in turn, had fallen from 16.2% in 2013 to 8.9% in 2017.

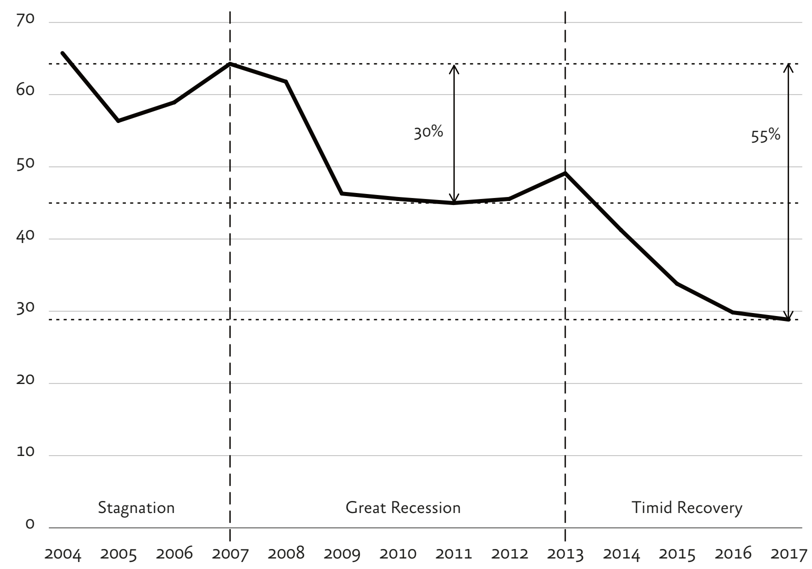
Figure 1.1 Real GDP growth and unemployment (in per cent)



Source: PORDATA.

As a major outcome of the crisis, there was a severe uptick in credit restrictions for Portuguese firms, with loans to non-financial firms falling by 30% between 2009 and 2012, as shown in Figure 1.2. By 2017, the reduction in loans reached an astonishing 55% mark.

Figure 1.2 Loans to non-financial firms (in 10^9 Euros)



Source: Banco de Portugal.

Carneiro et al. (2014) and Dias and Marques (2020) also analysed, at the micro-level, the consequences of the Great Recession on resource reallocation and productivity in Portugal. However, to the best of our knowledge, only Carreira and Teixeira (2016) explicitly analysed the nexus between financial constraints and business dynamics for the manufacturing sector (2004–2012). This study contributes to this strand of literature by providing manufacturing and service-wide evidence for a more extended period, up to 2017. Gouveia and Osterhold (2018) also analysed the resources sunk in zombie firms, but this study is the first to consider the determinants of the likelihood of recovery or exit of zombie firms, and to assess the 2012 reform of the insolvency regime.

A profound crisis such as the one generated by the COVID-19 pandemic requires proper policy design. If *productive cleansing* dominates, then countercyclical policies may entail the risk of hampering economic recovery. However, if deep economic crises generate *counterproductive destruction*, then countercyclical policies do have the potential to ameliorate the prospects of sustained long-run growth. We, therefore, hope that this book can serve as a guide to rigorous policy making.

1.2. Organisation of the book

The book is organised into eight main chapters, plus the Introduction (Chapter 1) and the Conclusion (Chapter 10). Chapter 2 reviews previous research on the effect of deep recessions on firm dynamics. Although economists have documented several stylised facts on firm dynamics, no pattern has been established in deep economic crises, for the simple reason that they are very rare.

The empirical analysis begins in Chapter 3, where we describe in detail the dataset and the variables used in the study. Chapter 4 looks at the productivity distribution and documents large and persistent differences in labour productivity levels across Portuguese firms. Since persistent heterogeneity in firm-level productivity may indicate the misallocation of resources, with negative effects at the aggregate level, in Chapters 5 and 6 we evaluate the business dynamics and its determinants, with a special emphasis on the role played by productivity and financial constraints.

Zombie firms are an exemplar of resource misallocation. In Chapter 7, we show that the resources sunk in zombie firms have risen during the crisis, thus hampering productivity growth. This chapter also contains an analysis of whether the transition of a firm out of the zombie status is associated with the implementation of downsizing and restructuring strategies. In Chapter 8, we go a step further and examine whether the 2012 reform of the insolvency regime was effective in strengthening the within-zombie selection, by promoting the recovery of the most productive firms and the exit of the least productive ones.

The sizable resource reallocation observed in the data does not generate aggregate productivity growth per se, as the process of productivity growth requires continuous productivity-enhancing reallocation. Chapter 9 quantifies the contribution of this reallocation process to the industry productivity growth, by decomposing the aggregate productivity growth into three components: within, covariance, and entry-exit.

Finally, Chapter 10 contains our concluding remarks, including possible policy implications.

Chapter 2
What do we know about firm dynamics in severe recessions?

2.1. Persistent differences in productivity levels across businesses

The economic literature on issues directly related to productivity can be roughly divided into two groups: one that documents and describes productivity dispersion, and one that examines the factors behind this dispersion. The first group of papers widely documents the large and persistent differences in firm productivity over time within narrowly defined industries. Syverson (2004b), for example, finds that within four-digit SIC industries in the U.S. manufacturing sector, plants in the 90th percentile of the productivity distribution produce almost twice as much output (with the same inputs) as plants in the 10th percentile. These highly productive firms today are more than likely to be highly productive tomorrow—regressing a producer's current TFP on its one-year lagged TFP. Foster et al. (2008) find an autoregressive coefficient in the order of 0.8.

Among the various explanations of the evolution of productivity dispersion, factors that have recently been examined include managerial ability, technology, human capital, and competition.[1] Given the importance of managers in efficiently directing the production process, it is reasonable to expect that two otherwise equal firms that only differ in the talents of their managers or in the quality of their practices will have different levels of success in production. For example, analysing management practices from over 11,000 firms in 34 countries, Bloom et al. (2016) found that differences in management practices account for about 30% of the total factor productivity (TFP) differences across firms, both between and within countries (see, also, Bloom et al., 2019). In the case of EU member states, Addison and Teixeira (2020) observed that a one-unit increase in the management practices indicator yields a 0.15 percentage point increase in the probability of the labour productivity of the establishment being in the highest growth group.

Other reasons for wide productivity differences across firms are the heterogeneity in technology and human capital. Dunne et al. (2004), for example, found that a substantial fraction of the rising dispersion in the productivity of U.S. establishments is accounted for by increasing productivity differentials across high and low computer investment per worker, and high and low capital intensity. Lopes and Teixeira (2013) also showed that human capital (i.e., schooling, training, and skills) has a positive effect on firm-level labour productivity, which explains part of the productivity differential across Portuguese firms.

A growing strand of the literature highlights the competitive environment that promotes well-functioning business dynamism, such as frictions in product and input markets (Syverson, 2004a, b; Bartelsman et al., 2013), institutional factors (McGowan et al., 2017a, b), and internationalisation (Melitz, 2003). We are, nevertheless, still far from fully understanding the determinants of productivity differences across firms. In this study we seek to shed further light on this relevant issue.

2.2. The relationship between productivity and resource reallocation

The Schumpeterian theory of creative destruction suggests that recessions are times in which outdated or relatively unprofitable techniques and products are more likely to be driven out of the market. In this context, Caballero and Hammour (1994) developed a model where recessions are shown to have a “cleansing” effect, according to which opportunity costs being lower than in normal times (e.g., the cost in terms of forgone output or sales due to investment activity is lower in recessions) generate a higher productivity-enhancing reallocation. However, the cleansing effect can be impaired by other means, such as financial and labour market frictions (Barlevy, 2002, 2003; Caballero and Hammour, 1996, 2005). For instance, credit market frictions may hurt high-productivity firms disproportionately during recessions, as such firms are likely to have higher financing constraints (Barlevy, 2003). Recessions are, therefore, likely to generate an additional “scarring” effect that could prevent the implementation of potentially superior projects facing financial constraints (Ouyang, 2009).

Several country studies reveal very substantial firm entry and exit flows. Entry and exit also tend to be highly (positively) correlated. The main reason is that the rate of early mortality among new firms is very high. Entrants are typically small, however, if successful, they tend to generate a rapid growth. On average, successful entrants double their initial size within six to seven years, although it may take more than a decade to achieve the average size of an established firm (Audretsch and Mata, 1995). Earlier research also found a close connection between firm dynamics and productivity, with exit, in particular, being much more common among low-productivity firms, and firm growth correlating positively with productivity (Carreira and Teixeira, 2011, 2016).[2]

The empirical literature has documented several stylised facts on firm dynamics using micro firm-level data. However, no pattern has been established in deep recessions for the simple reason that they are extremely rare. Hallward-Driemeier and Rijkers (2013) evaluated the effect of the Asian crisis (1997) using plant-level data from Indonesia however, despite the increase in the employment reallocation rate and a spike in firm exit, they found no evidence supporting the cleansing effect hypothesis. Productivity was less critical for firm survival during the crisis, while the risk of exit increased for financially constrained firms. In turn, Giroud and Mueller (2017) found that, during the Great Recession, highly leveraged U.S. establishments exhibited both substantial larger declines in employment and an increased risk of shutting down.

Interestingly, the results are not driven by neither firms being less productive nor overexpanding before the Great Recession. Similar results were found by Carneiro et al. (2014) and Carreira and Teixeira (2016) for the Great Recession (2008–2013) that hit the Portuguese economy following the 2008 financial crisis. These authors provided evidence that financially constrained firms were more vulnerable to the severe credit restrictions generated by the crisis, and that firms facing higher financial constraints destroyed jobs and exited at higher rates than firms that were not financially constrained. They also observed that the "catastrophic" job destruction flows, with nearly half of them being due to firm exit, made the Great Recession very different from all the previous business cycle downturns.

Business dynamics are expected to impact aggregate productivity growth, with changes in industry-level productivity arising either from within-firm productivity growth or resource reallocation, and low-productivity firms losing market share and shutting down in favour of more productive incumbents and new firms. Foster et al. (2001), for example, found that resource reallocation accounted for half of the US manufacturing productivity growth from 1977 to 1992, of which about 18% was due to the net entry effect. These results were confirmed by many authors for several countries, albeit at different magnitudes (e.g., Disney et al., 2003; Baldwin and Gu, 2006; Cantner and Krüger, 2008; Carreira and Teixeira, 2008; Fonseca et al., 2018).

An ongoing debate is whether the productivity-enhancing reallocation is, in fact, accelerated during recessions (the "cleansing" effect). Using data on large manufacturing firms between 1969 and 1996, Griffin and Odaki (2009) found that the weak Japanese productivity growth during the long 1990s stagnation was due to a large reduction in the within-firm effect rather than the absence of cleansing (i.e., the downsizing/exit of less productive firms). Foster et al. (2016) found that the Great Recession in the U.S. (2007–2009) was less productivity-enhancing in comparison with previous recessions and, in particular, that the extent of the cleansing effect among manufacturing firms was less pronounced than expected. Conversely, using firm-level data for Portuguese firms operating in all sectors, Dias and Marques (2020) found that the Portuguese financial crisis (2011–2012) was a period of intensified productivity-enhancing reallocation.

2.3. Misallocation of financial resources and distortion in firm selection

Bank forbearance is one of the channels through which credit market restrictions are able to hamper the normal functioning of market selection mechanisms, by allowing low-performance firms to survive. In fact, banks may be tempted to fund "zombie" firms—that is, mature firms that are debt-ridden and have no potential to repay their debt due to lack of profitability over an extended period—so that they look artificially solvent on their balance sheets. This behaviour was common among Japanese banks during the long stagnation at the end of the 20th century (Peek and Rosengren, 2005; Caballero et al., 2008).

Faced with a negative economic shock, the economic recovery is not only affected by the preservation of these less viable firms (zombie firms), which would not survive without "subsidised" loans, but also because these firms congest the market and, as a consequence, hamper the growth of more profitable projects (the "sclerosis" and "scrambling" effects, respectively; Caballero and Hammour, 1998, 2000). It should be noted that the latter effect is not less important than the former. In fact, most of the aggregate productivity growth is better explained by the within-firm effect than by the reallocation process (Bartelsman and Doms, 2000; Syverson, 2011). Effectively, Caballero et al. (2008) found that the increase in the share of zombie firms in an industry is associated with a reduction in aggregate productivity *and* an increase in the productivity gap between zombies and non-zombies. Throughout this process, there is a decline in investment and employment growth in non-zombie firms. Kwon et al. (2015) actually estimate that, without lending by banks to zombies, the annual aggregate productivity growth of the Japanese economy in the 1990s would have increased by one percentage point.

The study by Caballero et al. (2008) has been replicated in other countries with broadly similar results — e.g., Tan et al. (2016), for the Chinese economy (2005–2007); McGowan et al. (2018), for nine OECD countries (2003–2013);[3] Andrews and Petroulakis (2017), for 11 European countries (2001–2014);[4] and Gouveia and Osterhold (2018), for Portugal (2006–2015).

2.4. Insolvency regimes and the weakness of market selection

Efficient bankruptcy legislation plays a fundamental role in reducing distortions in market selection and in the allocation of resources, especially if it promotes the recovery of weak but viable firms with temporary financial distress *and* the exit of non-viable counterparts (McGowan et al., 2017a; 2018). The ability to differentiate viable from non-viable companies in insolvency events is, however, affected by asymmetric information in the capital market, as well as by the different incentives that managers, shareholders and creditors have in the ex-ante and ex-post stages of those events (Aghion, 1992; McGowan and Andrews, 2018).

Ownership and debt structures play a crucial role in the way these financial conflicts are resolved. For instance, a typical SME is characterised by few owners with almost no division between managers and shareholders. The debt is generally concentrated in banks that collateralise their financing against assets. Banks have, therefore, an important influence on SMEs' normal activities and on the resolution of insolvency events (Franks and Sussman, 2005; Bergthaler et al., 2015). Large companies are, in turn, characterised by complex ownership structures and greater debt dispersion (as well as lower bank dependence). As a result, the principal-agent conflict exists both between managers and shareholders, and between managers and creditors. Similarly, the complexity of ownership and debt structures is likely to complicate the resolution of insolvency conflicts, thus depressing the value of the firm (Franken 2004). For these reasons, the debate on insolvency legislation has been centred around which design is more likely to generate efficient results.

Creditor-oriented regimes promote agile liquidations and an immediate recovery of secured debt, accompanied by a quick dismissal of managers. These regimes also tend to preserve legal certainty, so the applicable redistributive regulation is the absolute priority rule, which emphasises the protection of the creditors' rights that were negotiated ex-ante. However, these regimes can motivate debtors to delay bankruptcy, which may also result in the excessive liquidation of viable firms (Adler et al., 2013).

Otherwise, debtor-oriented regimes allow for a reorganisation agreement that (i) maintains the manager in the office during the process ("debtor-in-possession"), (ii) completely stops the execution of creditors' collaterals ("automatic-stay-on-assets"); and (iii) permits deviations from the absolute priority rule ("loss-sharing"). Furthermore, reorganisation plans must be approved by creditors, although, in case of disagreement, the plan can be imposed by majority ("cram-down") (Aghion, 1992; Cirmizi et al., 2012; McGowan and Andrews, 2018). However, given that unsecured creditors and managers/shareholders can seek the business reorganisation in any circumstance, the recovery likelihood of unviable firms may also increase (Franken, 2004).

Evidence suggests that if there is the possibility of negotiating a reorganisation agreement, its success will be inversely proportional to the number of creditor classes involved (Kalay et al., 2007; Brunassi and Saito, 2018). On the other hand, the larger and older a company is, the more likely it will remain as a going-concern after the insolvency statement (García-Posada and Sánchez, 2018). And the higher the proportion of secured debt, the lower the probability of a reorganisation agreement being approved, even if the liquidation is inefficient. The opposite applies to unsecured debt (Ivashina et al., 2016; Brunassi and Saito, 2018).

International best practices suggest that a balance between creditors' and debtors' rights will maximise the ex-ante and ex-post efficiency of insolvencies (Djankov et al., 2008; Cirmizi et al., 2012; McGowan and Andrews, 2018). Actually, the OECD recommends that insolvency regimes should enable restructuring agreements, but with the following caveats: (*i*) managers should remain in their duties during the reorganisation period; (*ii*) creditors should not execute their collaterals immediately after insolvency is declared, albeit this period should be limited so as not to discourage future investment; (*iii*) deviations from the absolute priority rule to stimulate new financing should be allowed, but prioritising those who inject new funding only above unsecured creditors; and (*iv*) cram-down in the approval of the restructuring plans, although dissenting creditors should receive at least what they would receive in the liquidation event (McGowan and Andrews, 2018).

Efficient insolvency regimes can strengthen market selection not only through greater responsiveness at the exit margin, but also through increased competition driven by recovering zombies. Estimates by McGowan et al. (2017b) and Gouveia and Osterhold (2018) indicate that insolvency regimes that hinder corporate restructuring, more than reducing the recovery likelihood of relatively more productive zombies, increase the chances of a healthy company becoming a zombie. Regimes that are hostile to corporate restructuring can also affect the efficiency with which capital is reallocated, increasing the percentage of capital sunk in zombies (McGowan et al., 2017b), while hindering the technological catching-up of laggard firms (McGowan et al., 2017a). The results of Fukuda and Nakamura (2011) and Nakamura (2017) also suggest that, for listed Japanese firms between 1995 and 2004, strategies such as downsizing, technological restructuring and debt restructuring increased the recovery likelihood of zombies.

Chapter 3
A bird's-eye view of the dataset used in the study

3.1. Data source

The raw data used in this study was drawn from the Integrated Business Accounts System (SCIE). The SCIE is obtained from a process of statistical data integration based on various (annual) business statistical sources, namely the Simplified Business Information (IES), administered by the National Institute of Statistics (INE). The electronic delivery of the IES allows the entire population of Portuguese non-financial firms to fulfil their legal obligations on a single procedure, including the delivery of annual accounting and tax statements to the Tax Authority, and the provision of statistical information to the INE. In particular, it provides detailed information on the balance sheets and income statements of the firms.

Our sample includes all active corporations operating in Portugal in the manufacturing and services industries, excluding utilities, the financial sector and social services (i.e., education, health care, cultural and personal services), from 2004 to 2017. Some preliminary filtering of the raw data was required, namely: (*i*) we discarded observations with non-strictly positive values for gross output, total net assets and employment; (*ii*) we interpolated one-year reporting gaps linearly; and (*iii*) we winsorised all variables in the 1st and 99th percentiles. Our final sample comprises an unbalanced panel of 480,993 firms, totalling 3,388,941 year-firm observations. Table 3.1 provides the list of industries covered by our study, while Figures 3.1 and 3.2 show the number of firms and employees by sector.

Table 3.1 Number of firms and employment by industry

CAE-Rev.3	Industry	Number of firms			Employment		
		2004-07	**2008-13**	**2014-17**	**2004-07**	**2008-13**	**2014-17**
10–33	Manufacturing	39 390	36 171	35 393	742 756	638 547	638 222
41–43	Construction	40 647	36 933	31 304	374 991	328 795	242 381
45–47	Wholesale and retail trade	87 746	85 807	83 608	599 029	592 102	576 479
55–56	Accommodation and food services	27 170	29 032	31 082	192 572	208 302	227 798
68	Real estate	11 302	12 013	12 590	33 225	33 728	31 439
62–63; 69–82	Business services	34 899	42 793	47 990	373 166	438 002	486 087
	Total	**241 153**	**242 748**	**241 966**	**2 315 739**	**2 239 477**	**2 202 405**

Note: Annual average values.

3.2. Business demographics

This section provides an overview of the Portuguese business enterprise population. In 2017, Portugal's non-financial business sector consisted of 246.6 thousand active corporations with more than 2.35 million persons employed, representing an increase of 5.1% in the number of corporations from 2004 (see Figure 3.1). Between 2004 and 2017, employment rose by 4.2% (Figure 3.2).

Figure 3.1 Number of firms by sector (in 10^3)

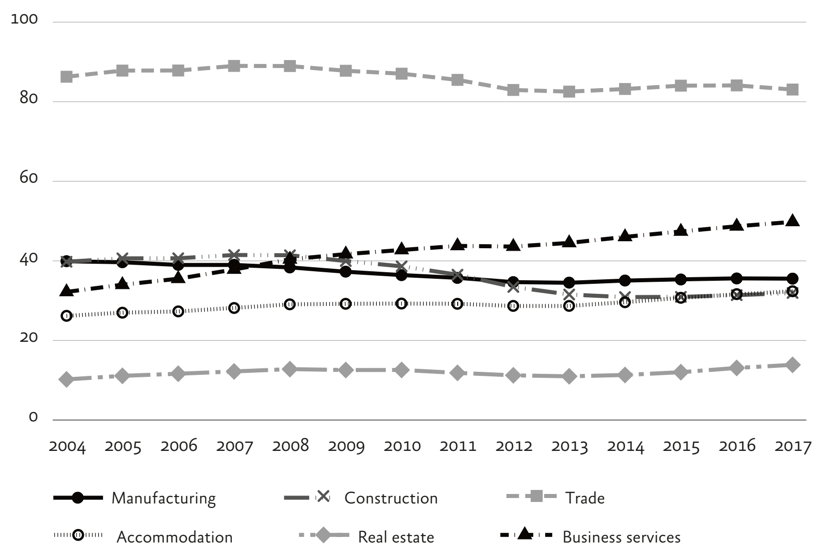
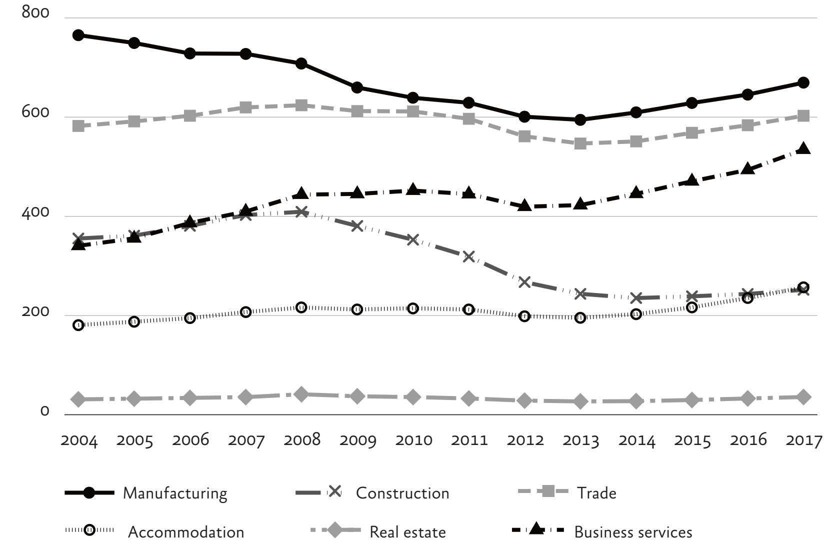


Figure 3.2 Persons employed by sector (in 10^3)

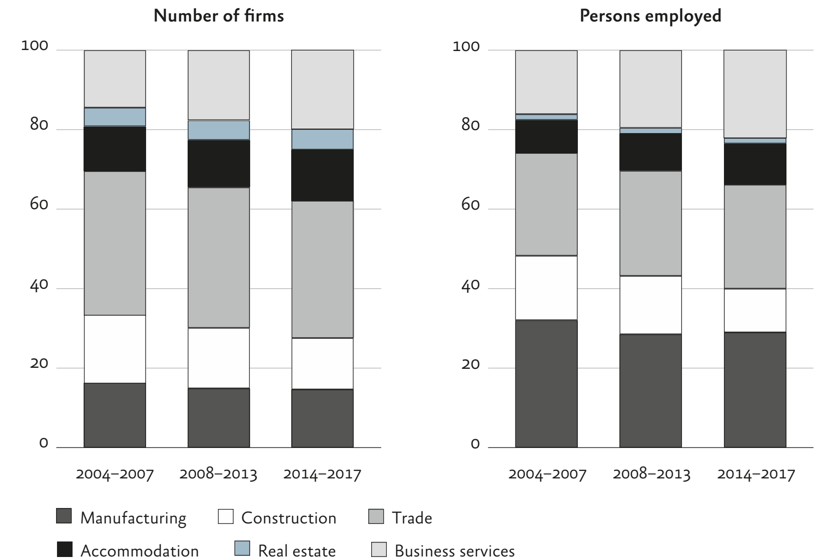


There are considerable differences across sectors. While the construction and manufacturing sectors lost 20% and 11% of their firms, respectively, over the entire period, the business services and real estate sectors increased their number of firms by 55% and 36%. This pattern remained valid for employment, albeit at different magnitudes (e.g., the growth rate of the business services sector was roughly 57%). It should be noted that the growth rate of employed persons in the Accommodation and food services sector was around 42% (with a growth of 24% in the number of corporations).

The trade sector was dominant, as measured by the highest proportion of active corporations. On average, more than one-third (more precisely, 35%) of non-financial corporations belong to this sector, concentrating about a quarter (26%) of the total number of persons employed (Figure 3.3). By contrast, only 15% of the corporations belong to the manufacturing sector; but they provided work for almost 30% of the persons employed (the highest proportion). Business services accounted for 17% of non-financial corporations and 19% of the workforce.

The average size of non-financial corporations (as measured in number of employees) was considerably higher in manufacturing than in services. Indeed, manufacturing firms employed an average of 18 persons compared to seven in the trade and accommodation sectors, and ten in the business services sector. In other words, about 64% of the manufacturing firms were micro-enterprises (i.e., employing less than ten persons), while the corresponding proportion of micro-enterprises in the trade, accommodation and business services sectors was close to 90% (Figure 3.4). The real estate sector accounted for the lowest average number of persons employed, with three employees per firm (97% of these firms were micro-enterprises). Finally, in Figure 3.4, we can also observe that about 29% of the manufacturing firms were small enterprises (with ten to 49 employees), 6% were medium-sized enterprises (with 50 to 249 employees), and the remaining 1% were large enterprises (with 250 or more employees).

Figure 3.3 **Structure of active corporations and employment by sector (in per cent)**



Regarding the geographical distribution, about two-thirds of all active corporations were located in the North (34%) and Lisbon (32%) regions (Figure 3.5). However, the specialisation of the two regions is clearly differentiated. More than one-half of the Portuguese manufacturing firms were operating in the North region, while Lisbon had the largest concentration of services firms (Table 3.2).

Figure 3.4 Firms' size by sector (in per cent)

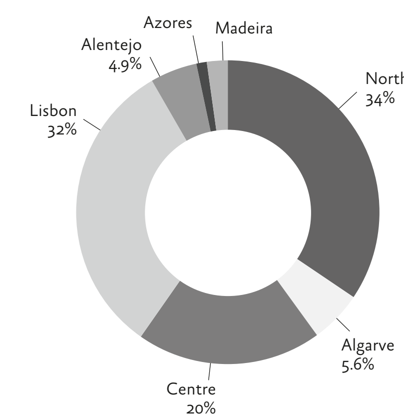
Notes: According to Decree-Law 372/2007 the size class of a firm is defined by its number of employees. Micro-firms employ less than ten persons, small firms employ ten to 49 persons, medium firms employ 50 to 249 persons, and large firms employ 250 or more persons. Pooled yearly values, 2004–2017.

Table 3.2 Geographical distribution of economic activities (in per cent)

Industry	North	Algarve	Centre	Lisbon	Alentejo	Azores	Madeira
Manufacturing	51.3	1.8	24.0	15.8	4.9	0.8	1.3
Construction	34.9	6.0	23.6	27.3	4.8	1.0	2.5
Trade	34.9	4.1	21.9	29.6	6.0	1.5	2.0
Accommodation	26.5	8.4	17.5	37.1	5.4	1.4	3.8
Real estate	29.5	9.1	15.4	39.1	3.7	0.8	2.3
Business services	29.3	4.3	16.2	42.8	4.4	1.1	1.8

Note: Pooled yearly values, 2005–2017.

Figure 3.5 Geographical distribution of firms



Note: Pooled yearly values, 2005–2017.

3.3. Enterprise births and deaths

The design of the survey allows us to identify the births and deaths of the firms. A birth occurs when a company starts from scratch and begins its operations until it reaches a combination of production factors. Each firm in the SCIE has a fixed identification number, which allows us to follow every single unit longitudinally. The births are identified when a new firm identifier appears in the database. However, there may be an initial investment period before the beginning of the production activities of a firm, which may extend beyond its first year of life. Following Carreira and Teixeira (2016), for any unit created in $t-\tau$, if there is no production activity observed between $t-\tau$ and t, then t is defined as the birth year. Births do not include dormant enterprises reactivated within two years. The other re-entry cases were treated as births.

In turn, a death is the termination of a corporation, which corresponds to the dissolution of a combination of production factors. In practice, firm death is flagged when a unit ceases its production activity permanently. Generally, this occurs simultaneously with the legal death of the firm (i.e., when the firm identifier disappears from the dataset). However, if a given unit ceases production in t and the legal death is in $t+\tau$, while no production is recorded between t and $t+\tau$, then t is coded as the year of death.

One of the weaknesses of the SCIE is the lack of information concerning mergers and acquisitions. In fact, we cannot distinguish a true exit from an exit generated by a merger or acquisition. However, this limitation is not likely to have an impact upon our results. According to Mata and Portugal (2004), mergers and acquisitions are rare and negligible events that do not exceed 1% of the exits.

In Chapter 5 we will analyse the entry and exit statistics in the Portuguese economy.

3.4. Measurement of productivity and key variables

As it is well known, productivity is the portion of a firm's output change that cannot be attributed to the accumulation of production factors. Our selected productivity measures are: firm-level total factor productivity, which equals the total output divided by the weighted average of the inputs, and labour productivity, which equals the total output divided by the units of labour.

To compute the firm-level total factor productivity (TFP), firstly, we estimate the factor elasticity parameters of a Cobb-Douglas production function for each industry (at two-digit CAE Rev.3 level), to allow for sector heterogeneity, using the following specification:

$$\ln Q_{it} = a_{it} + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln M_{it} + u_{it}, \tag{3.1}$$

where Q_{it} is the real gross output (production) of the i^{th} firm in year t; K_{it}, L_{it} and M_{it} are capital, labour and material (intermediate) inputs, respectively; and α, β and γ the respective factor elasticities.

To estimate Equation (3.1), we assume $u_{it} = \omega_{it} + \eta_{it}$, with ω_{it} denoting a firm-specific unobserved component, and η_{it} a residual term uncorrelated with input choices. Ordinary least-squares estimation produces inconsistent estimates due to the likely presence of simultaneity and selection biases. The simultaneity bias arises because input demand functions are also determined by the firm's knowledge of its productivity level. The selection bias is generated by endogenous exits, as smaller firms, with lower capital intensity, are more likely to exit. Assuming that ω_{it} is time-invariant, Equation (3.1) can be estimated using the least square dummy variable approach or the within transformation. However, the consistency of the fixed-effect model requires strict exogeneity of the included regressors, which is a non-realistic assumption (Griliches and Mairesse 1998). To overcome this problem, we estimate Equation (3.1) using the semi-parametric method proposed by Levinsohn and Petrin (2003), controlling for endogenous exits (Rovigatti and Mollis 2018). There are other alternative ways to estimate production function, however, they tend to generate similar TFP results, even if they produce somewhat different elasticities (van Biesebroeck 2008).[5]

The gross output is measured as the value of sales of goods and services, minus the value of purchases of goods for resale, adjusted for changes in inventory of final goods, self-consumption of own production and other operating revenues. It is deflated by the producer price index at the two-digit industry level obtained from INE. The labour input is measured as a 12-month employment average. Materials include the cost of materials and services purchased and were deflated by the GDP deflator index. Capital input is obtained by applying the perpetual inventory method to the change in total real assets (i.e., it includes not only tangible and intangible assets but also current assets, all of which important to the operation of the firm). In particular, for the first year in the time-series of a firm, we have deflated the book-value of total net assets by the GDP deflator index of that year, in order to derive the capital stock Kt. For subsequent years, when the assets rise, we deflate the increment by the GDP deflator index of the current year and add it to the $Kt-1$ to yield Kt. When the assets decline, we reduce Kt proportionately. Output and input variables are measured in constant 2011 Euro.

We also check the robustness of our results using labour productivity (LP). Labour productivity is defined as real gross value added (GVA) per worker, which is computed as the logarithmic difference between real GVA and employment (number of employees) and deflated by the producer price index (at the two-digit industry level). In Chapter 4, we will analyse the distribution and evolution of firms' productivity.

Operating cash-flow is computed as Earnings Before Interest, Taxes, Depreciation and Amortisation (EBITDA). Assets and debt are the book value of total (net) assets and total debt (i.e., the sum of long-term debt and debt in current liabilities). Leverage is computed using the book debt to assets ratio.

Chapter 4
Patterns of productivity dispersion

To analyse the relationship between productivity and reallocation, it is useful to start with some basic facts about the distribution of productivity across businesses. A ubiquitous feature of market economies is that there are large and persistent differences in productivity across firms, even within narrowly defined sectors (Bartelsman and Doms, 2000; Syverson, 2011). Not only are firms unequally productive but they also differ substantially. In this Chapter, following Yang et al. (2019), we model labour productivity dispersion as a Lévy alpha-stable distribution.

4.1. Measuring productivity dispersion

Although the use of Lévy alpha-stable distributions has a long history in finance and the physical sciences, its use in economics has so far been scarce. In the few exceptions, Gaffeo (2008, 2011) and Yang et al. (2019) conclude that the total factor and labour productivity data are better fitted by the Lévy alpha-stable distribution than by the Gaussian distribution. The use of this distribution is due to the heavy-tail of the productivity present in the data, which implies a higher prevalence of values at the tails than would otherwise be expected under a Gaussian distribution.

In our case, Trapani's test also supports the hypothesis that labour productivity at the firm level exhibits a heavy-tail, implying that choosing a distribution reliant on a finite second moment to model labour productivity is not appropriate (Trapani, 2016). The Lévy alpha-stable distribution is characterised by four parameters: α (tail exponent), β (skew), γ (scale), and δ (shift). Despite the variety of possible parametrisations for this distribution, we follow Nolan's So parametrisation and the corresponding interpretation (Nolan, 1998). We can then describe the Lévy alpha-stable distribution using its characteristic function:

$$\phi(t;\alpha,\beta,\gamma,\delta) =$$

$$\begin{cases} \exp\left\{i\delta t - (\gamma|t|)^{\alpha}\left[1 + i\beta \tan\left(\frac{\pi\alpha}{2}\right)\operatorname{sign}(t)\left((\gamma|t|)^{1-\alpha} - 1\right)\right]\right\}, & \alpha \neq 1 \\ \exp\left\{i\delta t - \gamma|t|\left[1 + i\beta\frac{2}{\pi}\operatorname{sign}(t)\log(\gamma|t|)\right]\right\}, & \alpha = 1 \end{cases} \tag{4.1}$$

The tail exponent $\alpha \in (0,2]$ indicates how prevalent tail values are (the lower the α the thicker the tail; and if $\alpha = 2$ then the distribution becomes a Gaussian distribution); $\beta \in [-1,1]$ is an index for the asymmetry of the distribution (the higher the value of β the more right-skewed the distribution; and $\beta = 0$ gives a symmetric density). The spread of the distribution over its support is determined by $\gamma \in [0,+\infty]$, and the central location, or the modal value of the distribution, is controlled by $\delta \in (-\infty,+\infty)$.

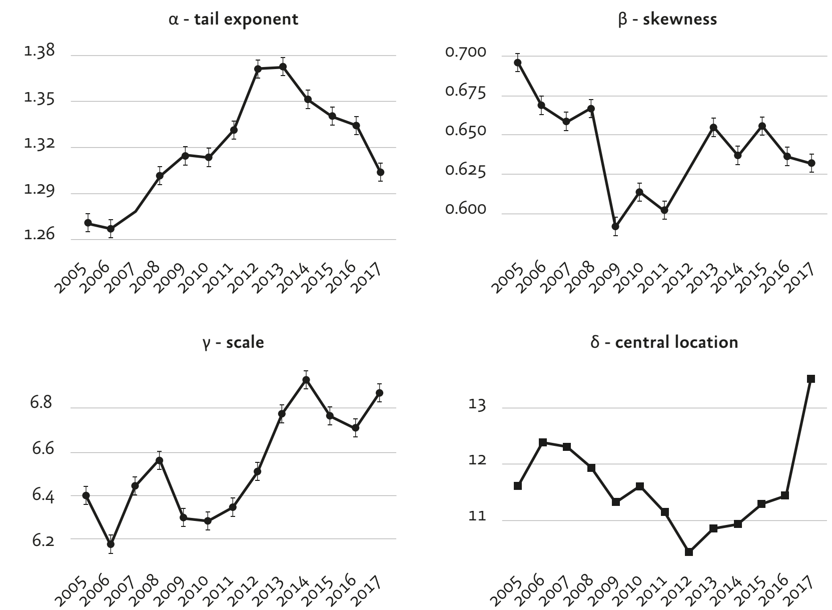
The Lévy alpha-stable distribution has a compelling advantage to analyse how firm-level labour productivity dispersion evolves over time, since its parametrisation allows us to separate what is happening at the tails from the overall width of the distribution. If we hold all other parameters constant while decreasing the tail exponent, α, the distribution will have a wider tail and a correspondingly narrower body. This increase in dispersion can be contrasted to what would happen if we maintained the tail exponent constant while increasing the scale parameter, γ. In this case, our distribution would become wider.[6] Thus, the two parameters capture two fundamental aspects of the nature of productivity dispersion that have been neglected in the literature. They are clearly critical for a proper assessment of the productivity dispersion patterns.

4.2. Dispersion by year

To understand the recent pattern of productivity dispersion in the Portuguese economy, we start by analysing the temporal evolution of the Lévy alpha-stable distribution parameters, with a focus on the tail and scale parameters (i.e., α and γ, respectively). Figure 4.1 shows the parameter estimates for a stable distribution fitted with yearly subsamples of firm-level labour productivity data, while Figure 4.2 presents the relative change of the parameters normalised with the initial year, 2005.[7]

The most noticeable aspect of how the parameter estimates have changed over time is that they closely track the recent Portuguese macroeconomic history, namely the Great Recession. It is not surprising then that the estimated parameters suggest a declining labour productivity performance, at least after 2005, reaching its lowest point around 2012 and 2013, and slowly improving subsequently. Indeed, as shown in Figure 4.1, the modal value δ exhibits a downward trend beginning in 2006 and ending in 2012, improving afterwards with a noticeable positive jump in 2017. The decline in productivity performance in the first part of the interval can also be observed in the skewness parameter, β, whose decrease implies that the asymmetry in the distribution of labour productivity has shifted to the left (i.e., towards lower values of labour productivity).

Figure 4.1 Estimated parameters for a Lévy alpha-stable distribution by year

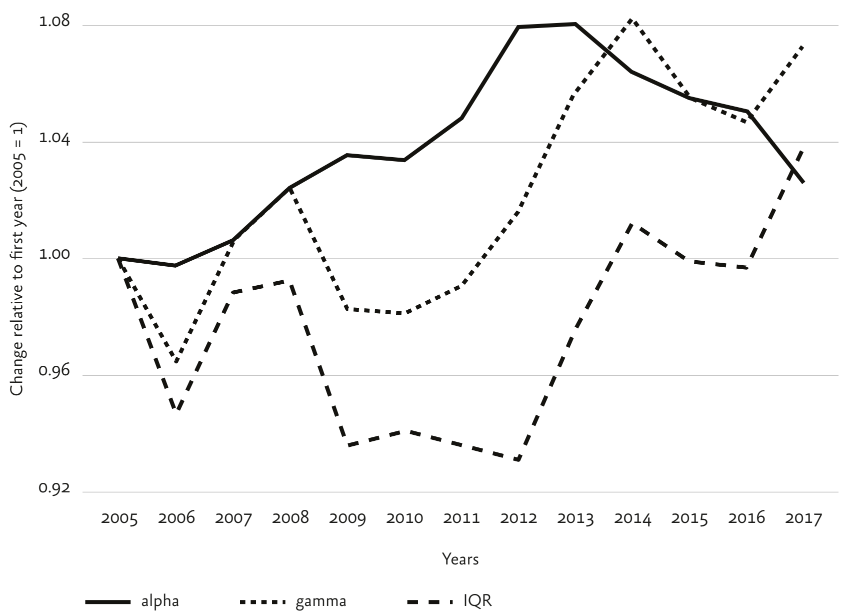


Notes: Stable law parameter estimation using McCulloch's quantile-based method for labour productivity data per year. The vertical bars represent the range of ±1 bootstrapped standard errors.

Figure 4.2 compares the relative change of the dispersion parameters with the Inter Quantile Ranges (IQR) over time. An interesting aspect is how the relative change in the IQR tracks the relative change in the scale parameter, γ. The changes in the behaviour of the distribution's tail do not seem to be mirrored in the interquantile range.

Looking at how the tail exponent has changed during this period, we can see that tail values became less pronounced starting in 2007 until 2013, where α reached its highest value. We recall that a higher value for the tail exponent indicates thinner tails and, therefore, the rising α, seen in Figures 4.1 and 4.2, implies that fewer firms were operating at the tails of the distribution.

Figure 4.2 Relative change of dispersion in labour productivity over time



Note: All the variables are normalised with the initial year.

While the tail exponent by itself does not distinguish between cases at opposite tails of the distribution, we expect a higher exponent to reflect a lower presence of firms operating at the right-tail end. In fact, from 2007 to 2013, there were fewer firms with comparatively high values of labour productivity. Observe that the distribution is skewed to the right, as reflected by the above zero values of β. This right-skewness implies a dearth of values to the left of the modal value, which is expected if we consider that firms operate in the market only if their productivity levels are higher than the threshold value below which they exit.

As of 2013, we observe a reduction in the tail exponent, which means an opposite effect, with more firms operating at the right-tail end of the distribution from that year on. Given the improved economic conditions, it would be counterintuitive to find an increasing share of firms with comparatively low values of labour productivity.

The scale parameter does not show any discernible trend until 2010, but after 2010 it begins ratcheting upwards until it reaches its peak in 2014. In contrast to α, it does not seem that the scale parameter entered a downward trend after reaching its peak value.

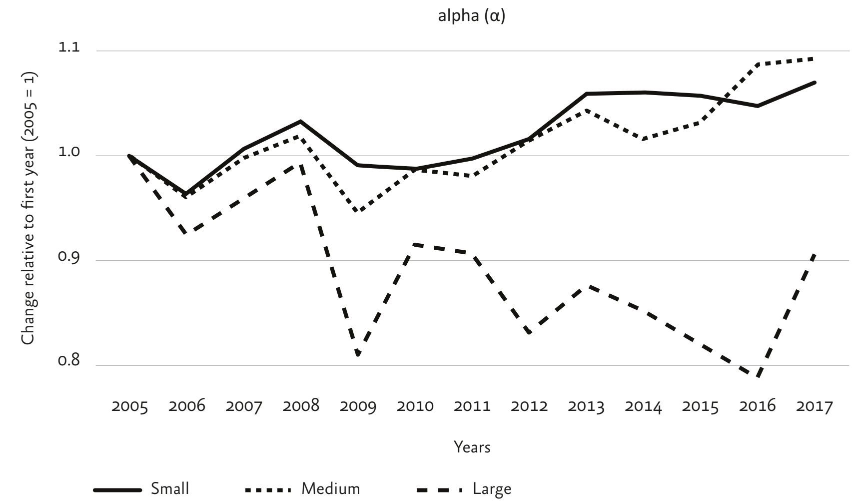
Interestingly, the relative change of the scale parameter, when compared with the IQR, is always higher, leading to different conclusions about the patterns of dispersion affecting the Portuguese economy in recent years. Thus, whereas the IQR suggests a decreased degree of dispersion from 2005 to 2014, the scale parameter indicates an increase in the dispersion levels after 2010.

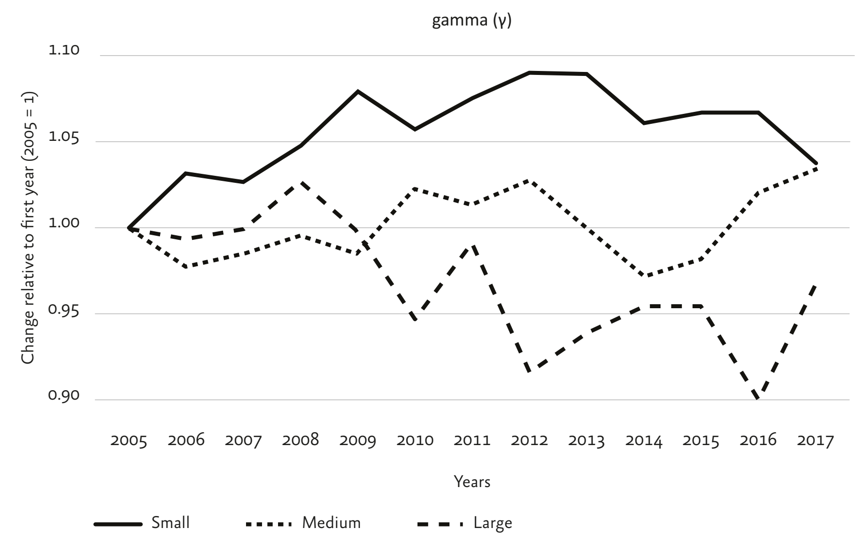
4.3. Dispersion by size

We now turn our attention to whether firms of different sizes have seen different dispersion patterns. To this end, we classify firms into a size category according to their number of employees (i.e., micro firms employ less than ten persons, small firms employ ten to 49 persons, medium firms employ 50 to 249 persons, and large firms employ 250 or more persons). Figure 4.3 shows the relative change of the dispersion parameters for small, medium, and large-sized firms.

The results suggest that whatever process drove the temporal evolution of labour productivity dispersion, it has affected firms differently based on their size. This can be seen most immediately by looking at how the relative change of the tail exponent α has evolved over time.

Figure 4.3 Relative change of dispersion in labour productivity over time by firm size





Note: See Figure 4.2 note.

Figure 4.3 shows that the tail exponent for small and medium-sized firms has roughly followed the same pattern seen in previous results whereby the tail exponent decreased before the crisis and increased during the Great Recession. This is, however, not the case for large-sized firms. The tail exponent for large-sized firms starts decreasing as of 2008, implying a more prominent presence of tail values.

The scale parameter, γ, shows approximately the same pattern. In effect, the relative scale parameter for small firms increases until 2009, maintaining its increased level of dispersion from that year onwards. However, large firms saw their scale parameter decrease quite prominently, suggesting two opposite patterns of dispersion, with an increase in the prominence of large firms operating at the tails and a larger number of large firms operating near their modal value. The relative scale parameter for medium-sized firms remained approximately constant, averaging out its fluctuations.

Overall, the results suggest that the productivity dispersion increased rather than decreased during the recession, which contrasts with what would be expected of the cleansing effect. As we hypothesised, frictions in product or factor markets seem to have hampered the productivity-enhancing resource reallocation, leaving room for the discussion in the following chapters.

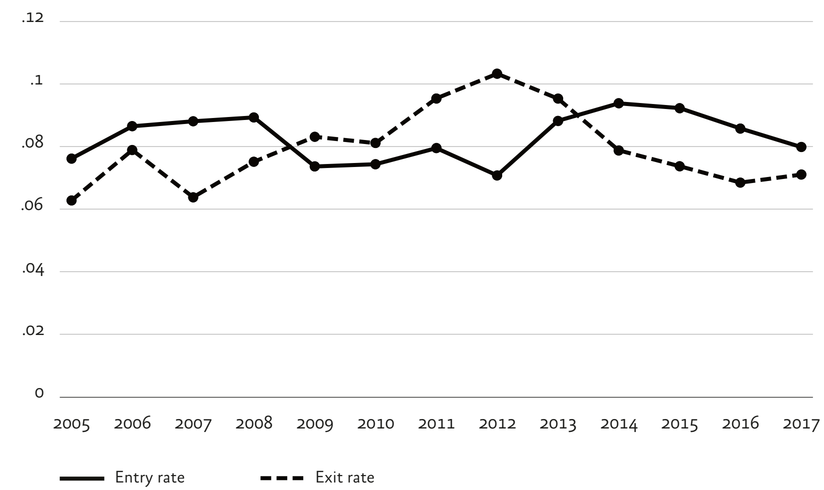
Chapter 5
How business' dynamics have changed during the recession

While reallocation per se does not yield productivity growth, the process of productivity growth requires ongoing productivity-enhancing reallocation. The reason is that there is a need for trial-and-error experimentation in both developing new products and processes and in adapting to changes in the economic environment. In this chapter, we examine the dynamics of Portuguese business in the 2004–2017 period, with a special emphasis on the role of productivity and financial constraints.

5.1. Entry and exit, and job flows

We begin with an overview of firm dynamics before, during, and after the Great Recession. Figure 5.1 shows the evolution of entry and exit rates for the entire Portuguese economy, while Table 5.1 reports their statistics by sector, splitting the sample into three sub-periods: stagnation (2004–2007), great recession (2008–2013) and recovery (2014–2017). Over the entire interval, the average annual entry and exit rates are 8.3 and 7.9%, respectively. In other words, about one in 12 firms operating in year *t* are newly-born firms, while approximately one in 13 will not be operating in the following year. Entry rates tended to fall during the Great Recession, while exit rates tended to rise, resulting in a negative net entry rate (entry minus exit). In particular, entry rates fell sharply from 8.9%, in 2008, to 7.4% in 2009 and 2010, reaching their minimum value of 7.1% in 2012. Exit rates, in turn, rose during the crisis period, peaking in 2012, at 10.3%, and then started to decline noticeably.

Figure 5.1 Entry and exit rates



Notes: See Table 5.1 notes for definitions. Aggregation weighted over two-digit industries (two-digit CAE Rev.3 level).

Firm entry and exit rates vary significantly across sectors. Table 5.1 shows that the annual entry and exit rates are somewhat higher in the service industries than in manufacturing. The recession seems to have had a small impact on the entry rates, except in the construction and real estate sectors, where the rates fell 1.4 and 2.5 p.p., respectively. In contrast, the exit rates rose sharply in most industries. After the crisis, the exit rates dropped sharply (on average, 1.8 p.p.) and the entry rates were, at least, in line with those reported during the pre-crisis period.

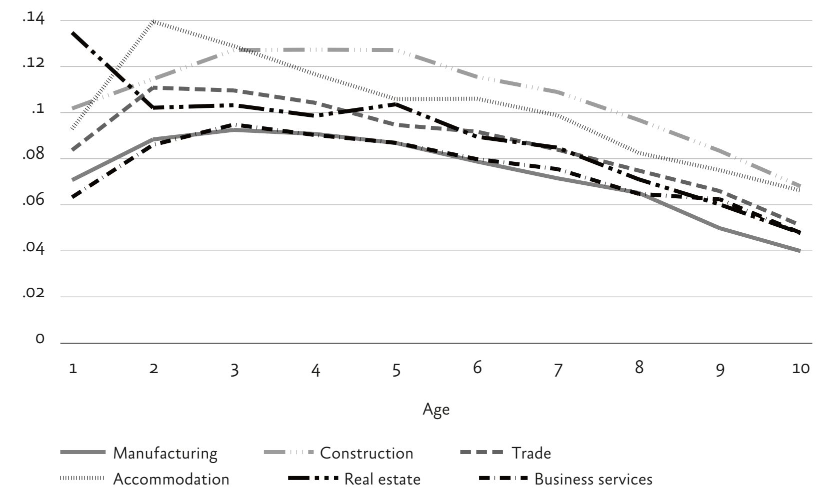
Table 5.1 Entry and exit rates by sector (in per cent)

	Stagnation (2004-2007)			Great Recession (2008-2013)			Recovery (2014-2017)		
Industry	Entry	Exit	Net entry	Entry	Exit	Net entry	Entry	Exit	Net entry
Manufacturing	5.4	6.3	-0.9	5.5	7.4	-1.9	6.1	5.5	0.6
Construction	8.8	7.9	0.9	7.4	11.8	-4.4	9.1	8.8	0.4
Trade	7.8	7.0	0.7	7.3	8.5	-1.2	7.5	7.1	0.4
Accommodation	8.7	6.5	2.2	9.1	8.9	0.2	11.6	8.8	2.8
Real estate	11.7	7.7	4.0	9.2	11.1	-1.9	13.1	7.8	5.3
Business services	11.3	6.0	5.3	10.6	7.8	2.8	9.9	6.9	3.0

Notes: Mean values over each sub-period. Entry and exit are defined as entry into the market and exit from the market. The reported entry (exit) rates are calculated as the ratio of entering (exiting) firms between years $t-1$ and t to the total number of firms in year $t-1$, as suggested by Dunne et al. (1988). Net entry is the difference between entry and exit.

The post-entry survival is also a key issue. Figure 5.2 shows the hazard rate of new firms by sector, while Table 5.2 compares the hazard rates after 2 and 4 years of life during stagnation (the base period) with the recession and recovery periods. There is evidence of a non-monotonic behaviour: the risk of exiting increases somewhat from the first to the second (trade and accommodation) or third (manufacturing, construction and business services) year of life, except in real estate, suggesting the existence of a "honeymoon" effect, according to which the firm's initial investment may entail insurance against failure in its early life (Fichman and Levinthal, 1991). After that, the hazard rates tend to decline gradually with age, but there are cross-industry differences—firms in the construction and accommodation sectors have the highest probabilities of failure within their first ten years of life.

Figure 5.2 Hazard rate of new firms by sector



Notes: The hazard function gives the probability of death at the age t conditional on surviving to t. Unweighted averages across industries.

Table 5.2 Difference in hazard rates between periods by sector (in percentage points)

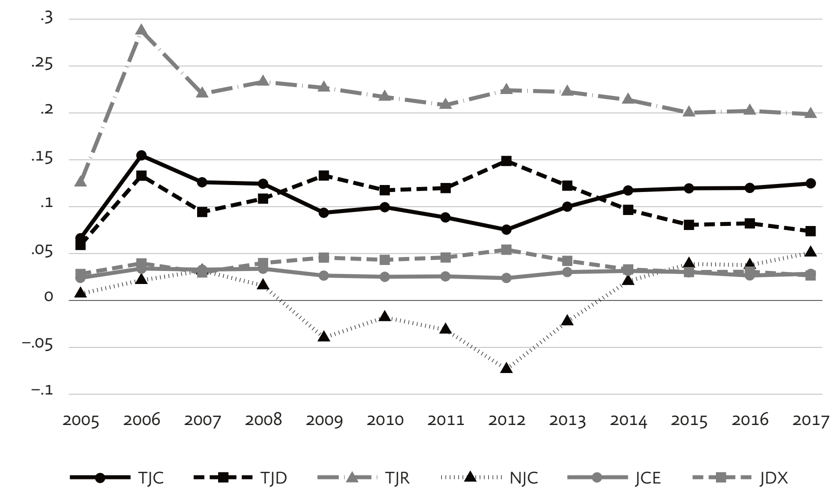
	Great Recession (2008-2013)		Recovery (2014-2017)	
Industry	2 years old	4 years old	2 years old	4 years old
Manufacturing	0.70	2.44	-3.18	-2.67
Construction	4.35	5.80	-2.08	-2.73
Trade	1.83	2.14	-3.41	-3.65
Accommodation	5.07	2.88	-1.56	-1.90
Real estate	3.26	4.69	-2.32	-2.52
Business services	1.69	2.56	-1.67	-1.90
t statistic	4.075***	5.670***	−7.527***	−9.635***

Notes: Difference in hazard rates between the current period and 2004–2007 (the base period), and *t* statistic of null hypothesis of no hazard rate difference. *** Statistical significance at the 0.01 level.

The risk of premature death increased during the Great Recession in all sectors. The probability of death for firms with two years old increased in the recession period between 0.7 p.p. (manufacturing) and 5.1 p.p. (accommodation and food services) when compared with the pre-crisis period (Table 5.2). The corresponding difference at four years old is even greater, ranging from 2.1 p.p. (trade) to 5.8 p.p. (construction). On the contrary, in 2014–2017, the premature failure rates were significantly lower than in 2004-2007.

Table 5.3 reports the rates of job creation and destruction by sector, while Figure 5.3 plots their evolution in the entire Portuguese economy. The average job creation and destruction rates were 10.8 and 10.5%, respectively. Net job creation was negative throughout the recession period, with a very pronounced net job loss in 2012 (7.3%)—in the manufacturing sector, the first shock was observed in 2009, with a net job loss of 7.1%. This high job loss was driven by both a slowdown in job creation and an uptick in job destruction. The job creation rate fell by 5.1 p.p. as of the beginning of the crisis, peaking in 2012, while the job destruction rate rose by 5.4 p.p. After 2013, the job creation rate reached pre-crisis figures, while the job destruction rate fell to a lower level. The correlation between net and gross job flows confirms that job creation is procyclical and job destruction is countercyclical.

Figure 5.3 Job flows



Notes: Total job creation rate (TJC), total job destruction rate (TJD), total job reallocation rate (TJR; *i.e.,* the sum of TJC and TJD, net job creation rate (NJC=TJC–TJD), job creation rate by entering firms (JCE), job destruction rate by exiting firms (JDX). See Table 5.3 notes for definitions. Aggregation weighted over two-digit industries.

Job reallocation patterns vary among industries—the job creation (destruction) rate ranges from 7.4% (8.4%) in manufacturing to 15.4%

(17.3%) in real estate (Table 5.3). Entry and exit play an important role in these flows—the share of job creation (destruction) accounted for by firm entry (exit) is approximately 30% (36%), on average.[8] Construction and real estate present the highest net job destruction during the recession period, 8.4% and 7.8%, respectively.

Table 5.3 **Job creation and destruction by sector**

	Stagnation (2004-2007)		Great Recession (2008-2013)		Recovery (2014-2017)	
Industry	**Rate (%)**	**Share due to entry/ exit**	**Rate (%)**	**Share due to entry/ exit**	**Rate (%)**	**Share due to entry/ exit**
			Job creation			
Manufacturing	7.2	0.263	6.7	0.248	8.6	0.182
Construction	16.0	0.311	11.8	0.311	15.2	0.241
Trade	10.6	0.297	8.4	0.320	9.7	0.268
Accommodation	12.9	0.360	11.4	0.390	16.1	0.349
Real estate	18.2	0.403	12.5	0.407	17.8	0.445
Business services	16.0	0.216	13.1	0.220	15.6	0.205
			Job destruction			
Manufacturing	8.8	0.368	9.9	0.385	5.7	0.376
Construction	12.0	0.416	20.2	0.364	14.3	0.318
Trade	8.5	0.387	10.5	0.385	6.9	0.382
Accommodation	8.5	0.361	12.6	0.315	9.4	0.381
Real estate	18.4	0.272	20.2	0.370	12.0	0.412
Business services	10.0	0.298	12.7	0.329	9.6	0.351

Notes: Mean values over each sub-period. JC (JD) denotes gross job creation (destruction) rate. The reported gross job creation (destruction) rate is calculated as the ratio of job creation (destruction) flows to the average employment of years t and t–1, as suggested by Davis et al. (1996).

5.2. Productivity and firm dynamics

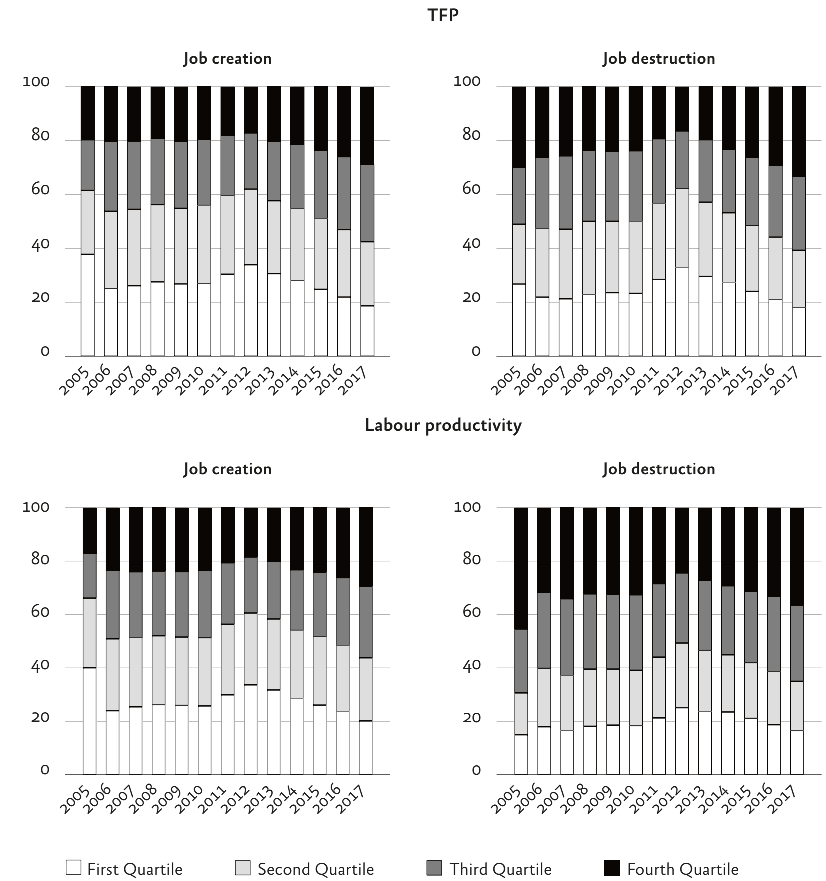
Given the sizeable firm turnover, a key issue is whether more productive units have replaced less productive firms; and if so whether the crisis generated any cleansing effect. Figure 5.4 shows the (labour and total factor) productivity gap among continuing and entering (exiting) firms. Given that firm productivity differs significantly across industries, we use the industry mean-adjusted indices to control for industry heterogeneity.

As can be seen, in their first (last) year of life entering (exiting) firms are, on average, less productive than continuing units by an 8 (13) and 57 (61) p.p. margin, in the TFP and labour productivity cases, respectively. This means that more productive units have replaced less productive firms. The relative productivity level required for entry seems to be higher during the crises period (i.e., a smaller productivity gap). Apparently, by comparing Figures 5.1 and 5.4, there are fewer, although more productive, entrants during the recession. However, note that the financial crisis may have inhibited potentially good projects to flourish, due to an increased difficulty in raising external investment funds. The productivity gap between continuing and exiting firms was also smaller in the Great Recession, possibly mirroring the cleansing effect of recessions.

Figure 5.4 Productivity gap among continuing, and entering and exiting firms

Notes: The graph shows the productivity difference between entering (exiting) and continuing firms. Firms' productivity was normalised by their average productivity over the sample period at the industry-level. Aggregation was weighted over two-digit industries by the firm's output and employment in the TFP and labour productivity cases, respectively.

Figure 5.5 Distribution of firms that created (destroyed) jobs by productivity level (in per cent)



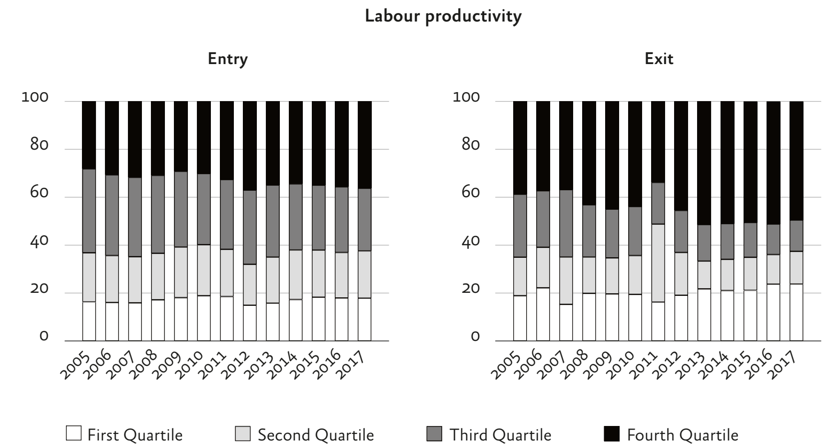
Notes: The graph shows the position of firms that created (destroyed) jobs within the industry productivity distribution. Aggregation unweighted over two-digit industries.

Another question we need to answer is, who creates and destroys jobs? Figure 5.5 provides the position of the firms that created (destroyed) jobs within the industry productivity distribution. Surprisingly enough, high-productivity firms (i.e., firms above the median) account for, at least, half of all the jobs destroyed. Furthermore, a substantial number of low-productivity firms have created jobs. The shares associated with the creation of jobs by low-productivity firms also rose in the peak of the crisis. A possible explanation for this unexpected finding is that firms tend to invest in less productive rather than more productive projects in times of tight financial constraints. Another explanation is that in periods of recession entrepreneurship may emerge as an alternative to unemployment (the so-called pushed-driven start-ups), and such alternatives are typically less productive (Rocha et al., 2018).

5.3. The role of leverage in firm dynamics

Unfavourable financial conditions during the Great Recession are likely to impose an additional barrier to entry and drive out otherwise good projects, especially in firms that are in more need of external financing. Figure 5.6 assigns each entering (exiting) firm by industry leverage-ratio distribution in the first (last) year of life. The main result that emerges is that nearly two-thirds of entering (exiting) firms have a leverage ratio higher than the industry median. This pattern is also generally true across industries—the fraction of entering (exiting) firms above the median is about 70% in manufacturing and trade and 60% in construction, real estate, and business services (Table 5.4). The proportion of exiting firms belonging to the fourth quartile increased, as expected, from around 38% in the pre-crisis period to 44% in the Great Recession, and then to 51% in the recovery period.

Figure 5.6 Distribution of entering and exiting firms by leverage ratio (in per cent)



Notes: The graph shows the position of each entering (exiting) firm within the industry leverage-ratio distribution. Leverage ratio was measured as the book debt over total assets. Aggregation unweighted over two-digit industries.

Highly leveraged new firms are much more likely to exit the market (fourth quartile in Figure 5.7). On average, 4.3% of new firms in the fourth industry-leverage quartile fail each year, while the corresponding rate for other quartiles is about 1.5% (i.e., a 2.8 p.p. difference). This result also holds when we look at the risk of new firms exiting across sectors (results not included). Moreover, as can be seen in Figure 5.8, the recession had a greater impact on highly leveraged new firms: (i) from 2004–2007 to 2008–2013, the hazard rate measured for 2-year and 4-year-old firms increased by 2.3 and 2.0 p.p., respectively, while in the other quartiles it only increased by 0.2 and 0.5 p.p., on average; (ii) in 2008–2013, the hazard rate gap between firms of the fourth quartile and other quartiles was also larger, 3.9

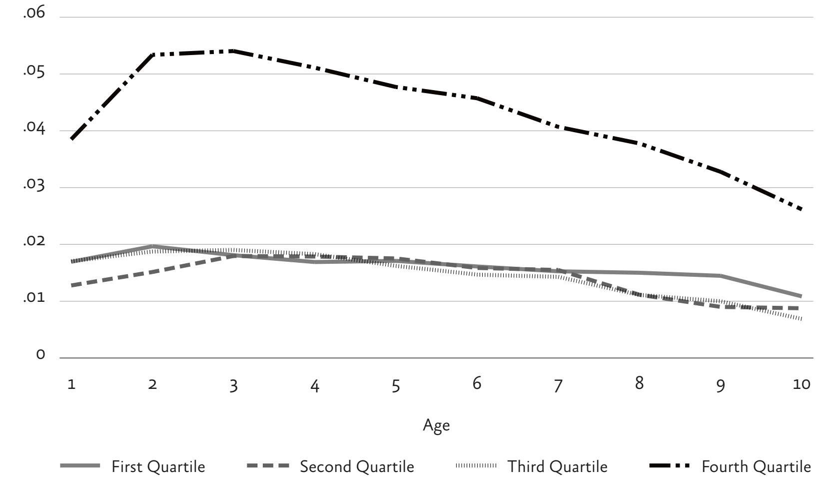
(2-year) and 3.8 (4-year) p.p., compared with the other periods. Finally, the main findings do not markedly change when we adopt the leverage ratio in the entry year rather than the year of death.

Table 5.4 Share of entering and exiting firms by leverage ratio (in per cent)

	Entry by quartile				Exit by quartile			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Stagnation (2004-2007)								
Manufacturing	11.2	16.4	34.9	37.5	18.0	12.8	25.9	43.2
Construction	21.8	19.3	27.0	31.8	20.2	11.1	34.2	34.5
Trade	12.2	17.2	37.9	32.8	16.6	18.6	23.1	41.6
Accommodation	15.9	29.9	44.1	10.0	21.4	30.4	20.4	27.9
Real estate	17.8	19.1	24.4	38.7	21.4	29.7	21.4	27.4
Business services	20.0	20.7	30.1	29.2	20.5	14.6	28.8	36.1
Great Recession (2008-2013)								
Manufacturing	14.0	16.8	31.1	38.2	17.1	14.1	19.8	49.1
Construction	23.3	19.9	23.8	33.1	23.5	18.5	20.1	37.8
Trade	13.5	17.1	34.0	35.5	16.5	17.6	16.8	49.0
Accommodation	14.0	23.4	40.9	21.7	17.6	22.7	22.4	37.3
Real estate	20.8	19.3	23.0	36.8	21.1	23.5	17.8	37.6
Business services	21.2	22.4	26.2	30.2	22.5	15.9	18.3	43.2
Recovery (2014-2017)								
Manufacturing	15.8	18.1	27.8	38.2	21.1	13.1	13.5	52.3
Construction	25.8	20.9	19.8	33.5	30.4	15.7	11.4	42.5
Trade	14.5	17.1	29.1	39.4	19.4	12.2	12.9	55.4
Accommodation	12.2	19.7	35.6	32.5	13.2	8.1	19.5	59.1
Real estate	23.3	20.3	21.2	35.3	27.2	18.9	15.2	38.7
Business services	20.9	23.1	24.0	31.9	28.4	15.5	12.6	43.5

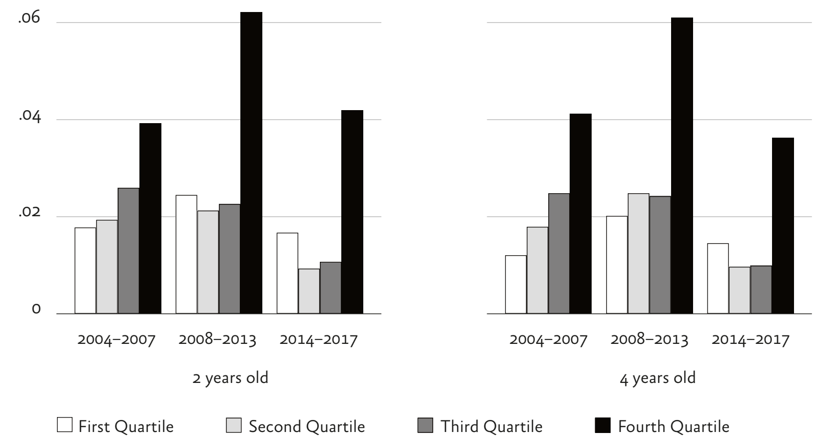
Notes: See Figure 5.6 notes. Mean values over each sub-period.

Figure 5.7 Hazard rate of new firms by leverage ratio



Note: Leverage ratio in the last year of life. Unweighted averages across industries.

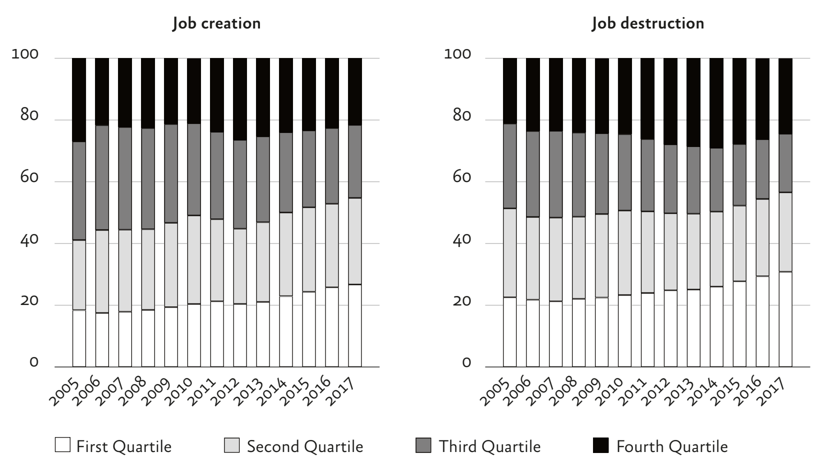
Figure 5.8 Hazard rate after two and four years of life by leverage ratio



Note: See Figure 5.7 note.

Figure 5.9 provides the relative position of the firms that created and destroyed jobs within the industry leverage-ratio distribution for the economy as a whole, while Table 5.5 provides these figures by sector. As can be seen, job creation significantly increased over time for firms below the industry-median leverage. In particular, the share of this group of firms rose by 14 p.p. from 2005 to 2017 (Figure 5.9). In the case of job destruction, the group of firms belonging to the fourth quartile increased by about 4 p.p. during the Great Recession. In the accommodation and food services, and real estate sectors the variation was even higher, 7 p.p.— that is, highly leveraged firms exhibited larger declines in employment during the recession. The findings remain valid across sectors, albeit at slightly different magnitudes (Table 5.5).

Figure 5.9 Distribution of firms that created (destroyed) jobs by leverage ratio (in per cent)



Notes: The graph shows the position of each firm that created (destroyed) jobs within the industry leverage-ratio distribution. Aggregation unweighted over two-digit industries.

Table 5.5 Share of firms that created (destroyed) jobs by leverage ratio (in per cent)

	Firms that created jobs by quartile				Firms that destroyed jobs by quartile			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Stagnation (2004-2007)								
Manufacturing	17.1	26.2	33.2	23.5	22.4	26.6	26.8	24.2
Construction	18.3	25.0	32.6	24.1	18.5	25.9	31.1	24.4
Trade	16.0	25.2	35.1	23.7	21.5	27.8	27.5	23.2
Accommodation	23.6	32.1	32.3	12.0	29.2	30.3	23.5	17.1
Real estate	18.1	23.9	28.7	29.3	23.3	26.1	27.4	23.2
Business services	17.5	24.7	32.8	25.1	18.3	24.9	30.3	26.5
Great Recession (2008-2013)								
Manufacturing	20.3	27.4	30.0	22.4	24.8	25.4	23.2	26.6
Construction	22.3	26.9	27.8	23.0	25.0	27.1	23.4	24.5
Trade	19.1	25.7	31.3	23.9	23.7	26.5	24.0	25.8
Accommodation	20.5	28.0	32.2	19.3	24.2	26.1	25.9	23.7
Real estate	19.8	23.3	25.6	31.3	19.7	25.7	24.2	30.3
Business services	19.4	26.8	29.6	24.2	19.8	25.3	26.5	28.3
Recovery (2014-2017)								
Manufacturing	27.4	28.9	24.7	19.1	30.1	24.7	19.2	26.0
Construction	29.5	27.9	21.1	21.4	33.6	25.9	17.4	23.1
Trade	25.1	27.2	24.9	22.9	29.2	25.1	19.2	26.5
Accommodation	20.3	24.7	27.2	27.9	21.1	20.5	21.9	36.5
Real estate	24.7	25.0	22.5	27.7	28.1	26.8	19.9	25.2
Business services	23.2	28.7	25.9	22.2	26.7	26.9	22.0	24.4

Notes: See Figure 5.9 notes. Mean values over each sub-period.

Chapter 6
Analysing the determinants of firm exit and growth

Credit constraints may have hampered the development of potentially superior projects by incumbents and new firms—the so-called "scarring" effect of recessions (Ouyang, 2009). In this chapter, we analyse in detail the role of productivity and financial constraints on firm exit and growth, distinguishing between young (i.e., firms who are less than ten years old) and mature firms. On average, about 10.4% of young firms fail each year, while the corresponding rate for mature firms is 6.4%.

6.1. Empirical model of firm exit and growth

We deploy the semi-parametric Cox Proportional Hazards model (CPH hereafter) to analyse the determinants of exit. The firm-specific, time-varying hazard rate $h_{it}(t)$—i.e., the instantaneous probability of death for firm i at time t conditional on having survived up to that point—depends on firm productivity, a set of firm financial characteristics, and firm and industry control variables.[9] Additionally, as in Hallward-Driemeier and Rijkers (2013), and Carreira and Teixeira (2016), we include interaction terms to assess how the relationship between exit and covariates of interest differs during the recession and recovery periods from the pre-crisis period, that is:

$$h_{it}(t) = h_0(t) \cdot \exp(\beta_{LP}\, p_{it} + \beta_{GR \cdot LP}\, p_{it} * GR_t + \beta_{R \cdot LP}\, p_{it} * R_t + \beta_{CF} cf_{it} + \beta_{GR \cdot CF} cf_{it} * GR_t + \beta_{R \cdot CF} cf_{it} * R_t + \beta_{Lev}\, lev_{it} + \beta_{GR \cdot Lev} lev_{it} * GR_t + \beta_{R \cdot Lev} lev_{it} * R_t + \beta_{\Delta Lev} \Delta lev_{it} + \beta_{GR \cdot \Delta Lev} \Delta lev_{it} * GR_t + \beta_{R \cdot \Delta Lev} \Delta lev_{it} * R_t + \beta_{\Delta y}\, \Delta y_{it} + \beta_L\, size_{it} + \delta_s + u_{it}), \tag{6.1}$$

where $h_0(t)$ is the baseline hazard function (i.e., the risk of failure when all the independent variables are zero); p_{it} denotes the log *productivity*, cf_{it} the *operating cash-flow*, lev_{it} the *leverage*, Δlev_{it} the *access to external finance*, *output growth* (Δy_{it}) and l_{it} the log *size* (i.e., the number of employees); GR_t is a dummy for the Great Recession (2008–2013) and R_t is a dummy for the recovery period (2014–2017); δ_s denotes industry fixed effect; and u_{it} is a standard error term (see Chapter 3 for a definition of all explanatory variables).

To examine whether a firm's growth, proxied by employment, became more strongly associated with productivity during the crisis, or whether it was determined by financial constraints, we estimate the following model:

$$g_{i(t+1)} = \gamma_{LP}\, p_{it} + \gamma_{GR \cdot LP}\, p_{it} * GR_t + \gamma_{R \cdot LP} p_{it} * R_t + \gamma_{CF}\, cf_{it} + \gamma_{GR \cdot CF}\, cf_{it} * GR_t + \gamma_{R \cdot CF} cf_{it} * R_t + \gamma_{Lev}\, lev_{it} + \gamma_{GR \cdot Lev}\, lev_{it} * GR_t + \gamma_{R \cdot Lev}\, lev_{it} * R_t + \gamma_{\Delta Lev}\, \Delta lev_{it} + \gamma_{GR \cdot \Delta Lev}\, \Delta lev_{it} * GR_t + \gamma_{R \cdot \Delta Lev}\, \Delta lev_{it} * R_t + \gamma_L\, size_{it} + \delta^s + \delta_t + v_i + u_{it}, \tag{6.2}$$

where δ_t denotes a year fixed effect and v_i is a firm-fixed effect. The employment growth rate $g_{i(t+1)}$ was computed as the logarithmic difference between employment for two consecutive years.

Under fairly general conditions, high-productivity firms are less likely to exit and more likely to grow. That is, β_{LP} is expected to be negative in the hazard rate model, while γ_{LP} is expected to be positive in the firm growth model. In turn, less financially constrained firms and firms with access to external finance, despite the future risk of indebtedness that external funding entails, are also less likely to exit and more likely to grow. Specifically, in the hazard rate model, we should expect $\beta_{CF} < 0$, $\beta_{Lev} > 0$ and $\beta_{\Delta Lev} < 0$, while the symmetric effect should be expected in the firm growth model, namely $\gamma_{CF} > 0$, and $\gamma_{\Delta Lev} > 0$.

The *x*-recession interaction term tells us whether variable x is over or underrepresented among exiting/growing firms relative to the pre-crisis period. Under the null hypothesis of no effect of recession, we have $e^{\beta_{GR \cdot x}} = 1$ (i.e., $\beta_{GR \cdot x} = 0$) or $\gamma_{GR \cdot x} = 0$.

Under the cleansing hypothesis, the crisis intensifies the creative destruction process, and hence recessions are expected to accelerate the downsizing and the exiting of low-productivity firms. Thus, in the hazard rate model, we expect $\beta_{GR \cdot LP} > 0$, that is, a higher risk of failure in the recession period than in the pre-crisis period for each level of productivity, given that $e^{\beta_{LP}} < e^{\beta_{LP \cdot x} + \beta_{GR \cdot LP}}$. In the firm growth model, we also expect $\gamma_{GR \cdot LP} > 0$, given that a recession possibly enhances the importance of productivity as a determinant of firm growth.

Financially constrained firms face tighter credit market restrictions during recessions, regardless of their level of productivity. Therefore, we expect the positive (negative) correlation between financial constraints and the hazard rate (firm growth) to be strengthened during the recession, in which case we will have $\beta_{GR \cdot CF} < 0$, $\beta_{GR \cdot Lev} > 0$, and $\beta_{GR \cdot \Delta Lev} < 0$, as well as, and $\gamma_{GR \cdot CF} > 0$. However, banks may also forbear bad debtors during the recession to protect their balance sheets, delaying their process of downsizing and exiting. In this case, we should expect an attenuation of the relationship between the independent and the dependent variables during the recession.

Some industries are relatively more in need of external finance than others. For example, the initial project scale, the gestation period, the cash harvest period, and the requirement for continuing investment differ substantially across industries (Rajan and Zingales, 1998). Thus, to investigate whether downsizing and exiting are higher in industries where firms reveal higher external financial needs, we rerun the empirical models (6.1) and (6.2), with the inclusion of the *industry financial dependence* (FD_s) interacted with firm financial constraints variables. The null hypothesis is that industry financial dependence does not affect the hazard rate and firm growth, that is $\beta_{FD \cdot CF} = \beta_{FD \cdot Lev} = \beta_{FD \cdot \Delta Lev} = 0$, and $\gamma_{FD \cdot CF} = \gamma_{FD \cdot Lev} = \gamma_{FD \cdot \Delta Lev} = 0$.

Our measure of industry financial dependence builds on the large literature on investment–cash flow sensitivity (ICFS) according to which if financially constrained firms cannot obtain external finance (or if it is available at a very high cost), then they must rely on their internally generated funds to finance investments. Therefore, the positive relationship between cash-flow and investment can be used as a measure of financial constraints (Carreira and Silva, 2010). We compute FD_s as the deviation from the mean cash-flow coefficient, that is $FD_s = [\phi^s_{CF} / (\sum_s \phi^s_{CF} / S)] - 1$, where the parameter ϕ^s_{CF} is the cash flow sensitivity of the investment for the industry *s*.[10]

The descriptive statistics and the correlation matrix of covariates are given in Tables 6.1 and 6.2, respectively.

Table 6.1 Descriptive statistics of covariates included in the hazard rate and firm growth models

Variables	Overall		Stagnation (2004-2007)		Great Recession (2008-2013)		Recovery (2014-2017)	
Exit dummy	0.080	(0.271)	0.070	(0.256)	0.090	(0.286)	0.071	(0.257)
Output growth (Δy_{it})	0.380	(1.169)	0.833	(1.361)	0.142	(1.033)	0.286	(1.015)
Employment growth (g_{it})	0.161	(0.488)	0.350	(0.572)	0.066	(0.430)	0.116	(0.423)
Log *TFP* (p_{it})	0.000	(0.669)	0.040	(0.601)	-0.043	(0.684)	0.025	(0.706)
Log *labour productivity* (p_{it})	0.000	(0.738)	0.037	(0.700)	-0.027	(0.751)	0.004	(0.753)
Cash-flow (cf_{it})	0.234	(0.621)	0.457	(0.677)	0.136	(0.535)	0.159	(0.627)
Leverage (lev_{it})	2.488	(3.973)	3.832	(4.885)	1.840	(3.213)	2.123	(3.661)
ΔLeverage (Δlev_{it})	-1.371	(3.805)	-3.444	(5.151)	-0.715	(2.918)	-0.801	(3.190)
Size ($size_{it}$)	1.204	(1.103)	1.285	(1.106)	1.198	(1.099)	1.133	(1.101)

Notes: Mean values and standard deviations (in parentheses). The variables were winsorised at the 1st and 99th percentiles. Pooled yearly values, 2005–2017.

Table 6.2 Correlation across covariates included in the hazard rate and firm growth models

Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1] *Exit dummy*	1							
[2] *Output growth*	-0.121*	1						
[3] *Employment growth*	-0.055*	0.747*	1					
[4] Log *TFP*	-0.164*	0.141*	-0.047*	1				
[5] Log *labour productivity*	-0.168*	0.057*	-0.052*	0.561*	1			
[6] *Cash-flow*	-0.060*	0.672*	0.609*	0.120*	0.127*	1		
[7] *Leverage*	0.019*	0.701*	0.668*	-0.103*	-0.126*	0.581*	1	
[8] *ΔLeverage*	-0.026*	-0.144*	-0.092*	-0.038*	-0.001*	-0.037*	0.097*	1
[9] *Size*	-0.132*	-0.048*	0.019*	0.055*	0.209*	-0.058*	-0.128*	0.056*

Notes: Pooled yearly values, 2005–2017. * Denotes statistical significance at the 0.01 level.

6.2. Determinants of firm exit

The results of CPH regression are presented in Table 6.3. The first three columns use TFP as a proxy for productivity, while the last three columns use the labour productivity variable. Since our dependent variable is the hazard rate, a negative coefficient implies that the corresponding variable reduces the instantaneous likelihood of exit, thus increasing the chances of survival. When analysing the results, we refer to the value $[1 - \exp(\beta_x)]$. 100 to describe the effect (in percentage) of variable x on the probability of death. The null that the parameters are jointly equal to zero is rejected at the 1% level—the corresponding Wald-test is given in the last row of Table 6.3.

As expected, higher levels of productivity reduce the hazard rate, while financially constrained firms seem to be more likely to shut down. The productivity coefficients are negatively signed and statistically significant at the 1% level, and in Column 1 (Column 4), a one-unit increase in the TFP (labour productivity) reduces the risk of exit by 19 (17)%.[11] The negative sign of the *cash-flow* and the *leverage change* coefficients indicate that, all else constant, a one-unit increase in internal or external funding reduces the risk of failure by 67 (63)% and 5 (5)%, respectively. In turn, the positive sign of *leverage* suggests that a one-unit increase in the degree of dependence on external funding increases the risk of failure by 2 (2)%. The risk of death is also lower for larger and growing firms.

Table 6.3 Determinants of firm exit: the crisis and recovery effects

	TFP			Labour productivity		
	All	Mature	Young	All	Mature	Young
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log productivity	-0.206***	-0.235***	-0.138***	-0.182***	-0.183***	-0.128***
	(0.006)	(0.007)	(0.014)	(0.004)	(0.005)	(0.008)
GR·Log *productivity*	0.117***	0.064***	0.121***	0.045***	0.030***	0.018**
	(0.007)	(0.008)	(0.015)	(0.005)	(0.006)	(0.009)
R·Log *productivity*	0.051***	-0.051***	0.067***	0.003	-0.030***	-0.028***
	(0.008)	(0.010)	(0.016)	(0.006)	(0.008)	(0.010)
Cash-flow	-1.100***	-1.284***	-0.999***	-0.998***	-1.156***	-0.932***
	(0.020)	(0.027)	(0.030)	(0.020)	(0.027)	(0.029)
GR·Cash-flow	0.167***	0.102***	0.116***	0.198***	0.124***	0.171***
	(0.018)	(0.025)	(0.028)	(0.017)	(0.025)	(0.027)
R·Cash-flow	0.167***	0.251***	0.077***	0.186***	0.253***	0.132***
	(0.019)	(0.031)	(0.029)	(0.019)	(0.030)	(0.028)
FD·Cash-flow	-2.551***	-3.272***	-2.368***	-2.223***	-2.813***	-2.095***
	(0.060)	(0.099)	(0.077)	(0.060)	(0.097)	(0.077)
Leverage	0.015***	0.024***	-0.067***	0.022***	0.036***	-0.071***
	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.011)
GR·Leverage	0.041***	0.038***	0.076***	0.044***	0.038***	0.085***
	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.011)
R·Leverage	0.035***	0.048***	0.068***	0.036***	0.043***	0.078***
	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.011)
FD·Leverage	0.058***	0.055***	-0.035	0.079***	0.092***	-0.026
	(0.015)	(0.021)	(0.022)	(0.015)	(0.021)	(0.022)
ΔLeverage	-0.053***	-0.066***	-0.025***	-0.053***	-0.065***	-0.024***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
GR·ΔLeverage	-0.014***	-0.049***	-0.004**	-0.014***	-0.048***	-0.004**
	(0.001)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)
R·ΔLeverage	-0.019***	-0.045***	-0.012***	-0.019***	-0.043***	-0.012***
	(0.002)	(0.007)	(0.002)	(0.002)	(0.007)	(0.002)
FD·ΔLeverage	-0.098***	-0.144***	-0.037***	-0.099***	-0.145***	-0.034***
	(0.006)	(0.011)	(0.008)	(0.006)	(0.011)	(0.008)
Output growth	-0.303***	-0.280***	-0.321***	-0.320***	-0.324***	-0.316***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Size	-0.471***	-0.487***	-0.379***	-0.443***	-0.460***	-0.358***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)
No. of observations	2,862,710	1,892,220	970,490	2,862,710	1,892,220	970,490
Log likelihood	-2493882	-1327662	-1029573	-2492209	-1327121	-1029517
Wald test	139938***	88570***	47574***	120157***	72691***	43858***

Notes: The Cox proportional hazard regression with 'ties' was handled with the Breslow method. Young firms are firms that have been operating for less than ten years. The log TFP (labour productivity) is normalised by the weighted average productivity by industry. *GR* is a dummy for the 2008–2013 period (Great Recession) and *R* a dummy for the 2014–2017 period (Recovery). *FD* denotes *industry financial dependence* and is computed as the deviation from the average ICFS coefficients. All regressions include two-digit industry dummies. Firm-cluster robust standard errors are given in parentheses. ***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

The previous determinants of exit seem to be less critical for young firms than for mature firms, while the risk of failure is higher for financially dependent industries. In fact, the *FD* interaction term indicates that the relationship between financial constraints and the hazard rate is larger for firms operating in industries with more unfavourable credit conditions as $\beta_{FD \cdot CF} < 0$, $\beta_{FD \cdot Lev} > 0$, and $\beta_{FD \cdot \Delta Lev} < 0$.

Did these patterns change during the Great Recession? There was, indeed, an attenuation of the link between productivity and survival during the recession, as the *GR-Productivity* interaction term was always significantly positive, but lower than the productivity coefficient. These results hold irrespective of the selected productivity measure. In TFP (Column 1), for example, the risk of failure was 10 p.p. higher during the Great Recession than during the pre-crisis period, all else constant. In other words, to reduce the hazard rate by 20% in 2008–2013 a two-unit increase in the TFP was required (comparing to the one-unit increase during the pre-crisis). Young firms were especially vulnerable to the crisis. While in the pre-crisis period a one-unit increase in the TFP reduced the risk of death by 13%, the same increase during the crisis only reduced it by 2%. This pattern is in accordance with the cleansing hypothesis, since firms with a lower productivity level have an increased risk of failure in recessions.

The effect of credit market restrictions on financially constrained firms is less clear. The *GR-Cash Flow* interaction term is always positive and statistically significant at the 1% level, which means an attenuation of the effect of cash-flow on a firm's probability of exit during the Great Recession. As expected, the results from the *GR-ΔLeverage* interaction term show that a firm's ability to raise external financing during the crisis is an additional factor for its survival. This relationship was particularly pronounced in the case of mature firms. As also expected, the leverage-hazard rate nexus was strengthened during the Great Recession (with a significantly positive *GR-Leverage* interaction term), which means that the risk of death did increase.

During the recovery period, and contrary to our expectations, the financial constraint effect observed during the crisis was not reversed, as shown by the behaviour of the *R-x* interaction terms. One plausible explanation is that credit market restrictions remained strong after the crisis, as observed in Figure 1.2.

In order to investigate the effect of credit market restrictions on the financially vulnerable firms during the Great Recession, we re-estimate the CPH model for 2008–2017, using a sub-sample of firms operating in 2007 and controlling for the pre-crisis leverage ratio. The results are presented in Table 6.4. As can be seen, the higher the leverage ratio in 2007, the greater the risk associated with the probability of a shutdown. For example, in the TFP (labour productivity) estimate, firms in the fourth quartile face a hazard 51.1% (49.2%) greater than firms in the first quartile, all else constant.

6.3. Determinants of Firm growth

The results for the employment growth estimations of model (6.2) are presented in Table 6.5. The null hypothesis of a random effects model is rejected (in favour of the fixed effects case), as well as the null of homoscedasticity.[12] The null that the parameters are jointly equal to zero is also rejected at the 0.01 level (see the *F* statistic in the penultimate row of Table 6.5).

Table 6.4 Determinants of firm exit: controlling for the pre-crisis leverage ratio

	TFP			Labour productivity		
	All	Mature	Young	All	Mature	Young
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log *productivity*	-0.169***	-0.213***	-0.085***	-0.161***	-0.169***	-0.138***
	(0.005)	(0.006)	(0.008)	(0.003)	(0.003)	(0.005)
Cash-flow	-1.090***	-1.224***	-0.908***	-0.948***	-1.080***	-0.770***
	(0.022)	(0.029)	(0.035)	(0.022)	(0.029)	(0.035)
FD·Cash-flow	-3.162***	-3.557***	-2.509***	-2.737***	-3.086***	-2.175***
	(0.097)	(0.120)	(0.161)	(0.096)	(0.120)	(0.159)
Leverage	0.021***	0.032***	0.016*	0.033***	0.044***	0.025***
	(0.005)	(0.006)	(0.009)	(0.005)	(0.006)	(0.009)
FD·Leverage	-0.007	0.018	-0.045	0.026	0.054**	-0.018
	(0.021)	(0.025)	(0.041)	(0.021)	(0.025)	(0.040)
Leverage 2007: Q2	0.128***	0.124***	0.041*	0.124***	0.120***	0.040
	(0.009)	(0.010)	(0.025)	(0.009)	(0.010)	(0.025)
Leverage 2007: Q3	0.246***	0.233***	0.074***	0.243***	0.232***	0.073***
	(0.009)	(0.010)	(0.023)	(0.009)	(0.010)	(0.023)
Leverage 2007: Q4	0.413***	0.314***	0.182***	0.400***	0.308***	0.172***
	(0.009)	(0.011)	(0.021)	(0.009)	(0.011)	(0.021)
ΔLeverage	-0.057***	-0.129***	-0.019***	-0.057***	-0.122***	-0.019***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.008)	(0.005)
FD·ΔLeverage	-0.095***	-0.293***	-0.014	-0.092***	-0.271***	-0.011
	(0.016)	(0.032)	(0.020)	(0.017)	(0.033)	(0.020)
Output growth	-0.274***	-0.263***	-0.294***	-0.309***	-0.311***	-0.304***
	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)	(0.005)
Size	-0.477***	-0.495***	-0.379***	-0.451***	-0.470***	-0.356***
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)
No. of observations	1,621,206	1,309,592	311,614	1,621,206	1,309,592	311,614
Log likelihood	-1302740	-874660	-359885	-1301976	-874315	-359619
Wald test	86240***	64388***	18617***	75786***	54038***	17935***

Notes: Cox proportional hazard regression for the 2008–2017 period, using a sub-sample of firms operating in 2007. "*Leverage* 2007" is the leverage ratio in 2007; Q2, Q3 and Q4 are the dummy variables for quarters 2, 3, and 4, respectively. All regressions include two-digit industry dummies. Firm-cluster robust standard errors are given in parentheses. ***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6.5 Determinants of employment change: the crisis and recovery effects

	TFP			Labour productivity		
	All	Mature	Young	All	Mature	Young
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log *productivity*	0.048***	0.049***	0.047***	0.039***	0.040***	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GR·Log *productivity*	0.010***	0.009***	0.013***	0.013***	0.013***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R·Log *productivity*	0.018***	0.014***	0.026***	0.024***	0.022***	0.026***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Cash-flow	0.056***	0.064***	0.038***	0.054***	0.059***	0.039***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
GR·Cash-flow	0.024***	0.034***	0.015***	0.021***	0.030***	0.015***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
R·Cash-flow	0.039***	0.044***	0.035***	0.033***	0.036***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FD·Cash-flow	0.154***	0.191***	0.064***	0.136***	0.162***	0.066***
	(0.009)	(0.011)	(0.017)	(0.009)	(0.011)	(0.017)
Leverage	0.001	-0.004***	0.011***	0.001	-0.003***	0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
GR·Leverage	-0.003***	-0.003***	-0.007***	-0.003***	-0.003***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R·Leverage	-0.005***	-0.004***	-0.010***	-0.004***	-0.004***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FD·Leverage	-0.029***	-0.040***	-0.009	-0.027***	-0.039***	-0.010
	(0.003)	(0.004)	(0.007)	(0.003)	(0.004)	(0.007)
ΔLeverage	0.002***	0.007***	-0.006***	0.002**	0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
GR·ΔLeverage	-0.000**	0.002***	-0.001***	-0.000**	0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R·ΔLeverage	-0.001***	0.002***	-0.001***	-0.001***	0.002**	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
FD·ΔLeverage	0.025***	0.033***	0.017***	0.023***	0.032***	0.016***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Size	-0.337***	-0.305***	-0.452***	-0.341***	-0.309***	-0.455***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
No. of observations	2,069,003	1,466,464	602,539	2,069,003	1,466,464	602,539
No. of firms	329,731	198,491	150,190	329,731	198,491	150,190
F statistic	2374	1605	937.2	2405	1627	934.8
R^2 (within)	0.195	0.176	0.263	0.196	0.177	0.263

Notes: Fixed-effects regression of model (6.2). Young firms are firms that have been operating for less than ten years. The log labour productivity is normalised by the weighted average productivity by industry. *GR* is a dummy for the 2008–2013 period (Great Recession) and *R* a dummy for the 2014–2017 period (Recovery). *FD* denotes *industry financial dependence* and is computed as the deviation from the average ICFS coefficients. All regressions include two-digit industry dummies, year dummies and a constant term. Firm-cluster robust standard errors are given in parentheses. ***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

As expected, productivity has a positive and statistically significant effect on employment change. The higher the *Cash-flow,* the higher the employment growth. Highly leveraged firms, in turn, seem to grow at a higher rate, although the effect appears to be reversed under tight credit conditions. Larger firms grow slower. Lastly, the general pattern for the full sample holds for both mature and young firms.

The crisis seems to have strengthened the relationship between productivity and job creation (with a significantly positive *GR-Productivity* interaction term), which is consistent with the cleansing hypothesis, and also the positive links between cash-flow and employment growth. On the other hand, the *GR-Leverage* interaction term was negative, statistically significant, and had a greater magnitude than during the pre-crisis period, implying that highly leveraged firms have grown slower during the crisis. Before the crisis, highly leveraged young firms grew at a higher rate, which can be attributed to the effect of past, or initial, investment. However, these firms currently reveal a preference for internal funds over debt (considering the negative *ΔLeverage* and *GR-ΔLeverage* coefficients).

Firms that were financially vulnerable before the crisis tended to grow slower during the Great Recession. As shown in Table 6.6, the estimated coefficients for the upper 2007 leverage quartiles are negative and statistically significant.

Table 6.6 **Determinants of employment change: controlling for the pre-crisis leverage ratio**

	TFP			Labour productivity		
	All	Mature	Young	All	Mature	Young
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log *productivity*	0.046***	0.044***	0.052***	0.047***	0.046***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Cash-flow	0.112***	0.129***	0.079***	0.097***	0.111***	0.071***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
FD·Cash-flow	0.271***	0.329***	0.136***	0.220***	0.268***	0.110***
	(0.012)	(0.014)	(0.025)	(0.012)	(0.014)	(0.025)
Leverage	0.004***	-0.001	0.008***	0.005***	0.000	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FD·Leverage	0.003	-0.010***	0.015**	0.006**	-0.007**	0.016**
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)
Leverage 2007: Q2	0.005***	0.004***	0.009***	0.004***	0.003***	0.008**
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
Leverage 2007: Q3	-0.000	0.001	0.004	-0.002**	-0.001	0.001
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
Leverage 2007: Q4	-0.009***	-0.007***	0.003	-0.008***	-0.007***	0.003
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
ΔLeverage	-0.001**	0.006***	-0.002**	-0.002***	0.005***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FD·ΔLeverage	-0.005**	0.013***	-0.007**	-0.007***	0.011**	-0.008***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
Size	-0.058***	-0.048***	-0.098***	-0.063***	-0.052***	-0.102***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)

Variables	TFP All (1)	TFP Mature (2)	TFP Young (3)	Labour productivity All (4)	Labour productivity Mature (5)	Labour productivity Young (6)
No. of observations	1,025,411	789,126	236,285	1,025,411	789,126	236,285
No. of firms	209,732	156,612	53,120	209,732	156,612	53,120
R^2 (within)	0.115	0.092	0.188	0.109	0.087	0.180

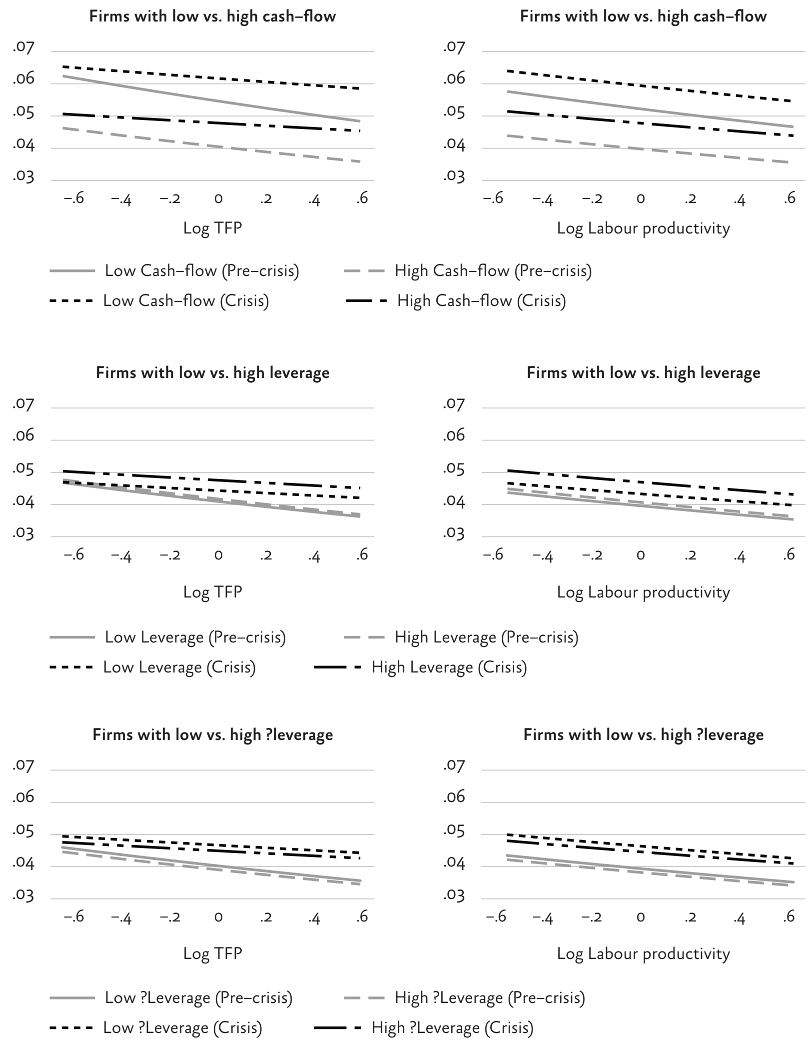
Notes: Fixed-effects regression of model (6.2) using a sub-sample of firms operating in 2007. "*Leverage* 2007" is the leverage ratio in 2007; Q2, Q3 and Q4 are the dummy variables for quarters 2, 3, and 4, respectively. See Table 6.5 notes. All regressions include two-digit industry dummies, year dummies and a constant term. Firm-cluster robust standard errors are given in parentheses. ***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

6.4. Post-estimation analysis

The results outlined above point to sizeable effects of credit constraints on firm dynamics, especially during the Great Recession. Financially constrained firms may have either shrunk or exited the market, even when they were sufficiently productive to survive and grow in the absence of such constraints. To illustrate that financial constraints in conjunction with an unfavourable economic cycle are likely to generate a long-lasting destructive process, we derived the hazard and growth rates for constrained vs. unconstrained firms in pre-crisis vs. crisis periods by productivity level, based on the estimations reported in Columns 1 and 4 of Tables 6.3 and 6.5. Figures 6.1 and 6.2 show these post-estimation results, assuming a scenario of neutral *FD*, industry and year variables (i.e., with the *FD*, industry and year variables set to zero). The remaining variables were set at the corresponding sample mean.

Productivity seems to have a lower impact on the hazard rate than financial constraints. Depending on the financial variable of interest, the difference in the predicted hazard rate between low and high-productivity firms (the 25th and 75th percentiles, respectively) is about 0.5 (0.4) p.p. and 0.3 (0.2) p.p. in the pre-crisis and crisis periods, respectively (Figure 6.1). In the case of cash-flow, for example, the difference in the hazard rate between low and high-cash flow firms (the 25th and 75th percentiles, respectively) is, on average, about 1.4 p.p. During the crisis period, the productivity of a high-cash flow firm with low productivity would have to increase to the 99th percentile in order to keep the predicted exit risk unchanged when moving to the low-cash flow state (in both productivity measures). This means that moving from an unconstrained to a constrained state during the crisis had an impact on the exit risk equivalent to reducing the productivity from the 99th to the 25th percentile. In the pre-crisis period, the shift in TFP (labour productivity) was smaller, from the 41st (45th) to the 25th percentile.

Figure 6.1 Estimated hazard rate: productivity versus financial constraints



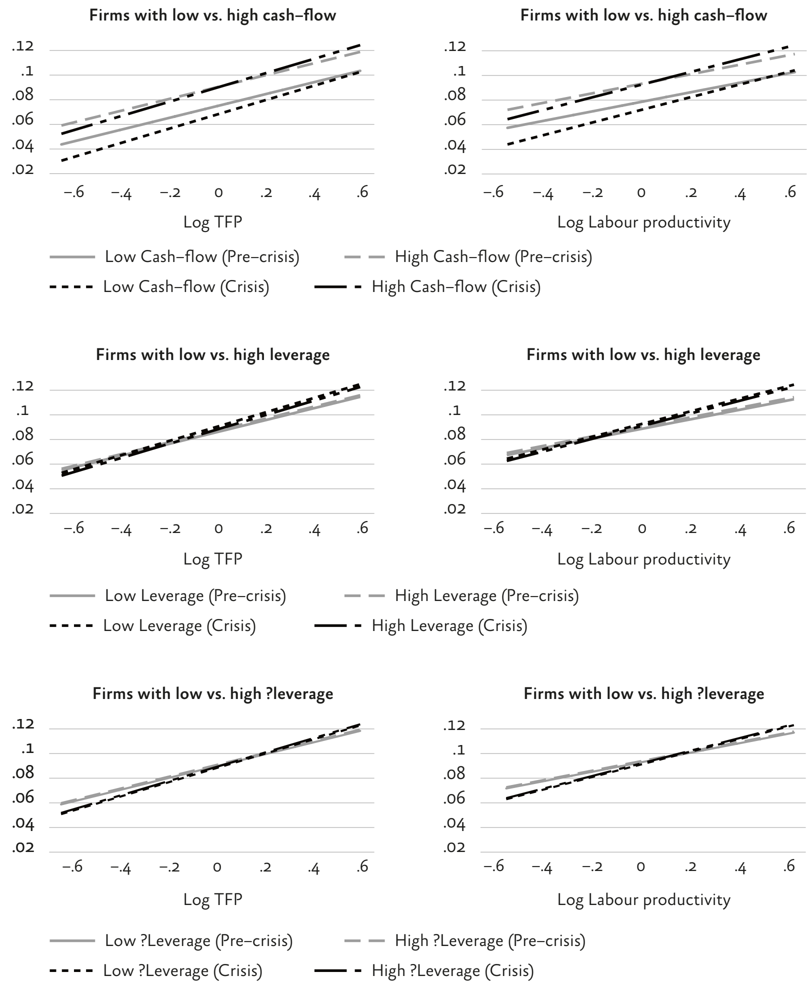
Notes: The graphs show the estimated hazard rates for constrained vs. unconstrained firms in the pre-crisis vs. crisis periods by productivity level, based on the estimations reported in Column 1 of Table 6.3, assuming a sample mean for variables of no interest and a scenario of neutral *FD*, industry and year.

As we have seen, the risk of death increases with the degree of corporate indebtedness. During the crisis, the difference in the hazard rate between high and low-leverage firms increased by 0.2 and 0.3 p.p. in TFP and labour productivity, respectively. Furthermore, the impact of moving from low to high-leverage ratios during the crisis on the exit risk was equivalent to reducing TFP (labour productivity) from the 91st (81st) to the 25th percentile.

Finally, the predicted hazard rate confirms that a firm's ability to raise external financing (proxied by *ΔLeverage*) during the crisis is crucial to reduce its probability of exiting the market. Overall, the post-estimation results seem to support the hypothesis that viable but financially constrained firms have been forced to exit during the Great Recession.

Regarding employment growth, Figure 6.2 confirms that the productivity effect has been strengthened during the recession, supporting the cleansing hypothesis. In effect, in the crisis period, high-TFP (labour productivity) firms grew 2.9 (2.6) p.p. more than low-productivity units, via-à-vis 2.4 (2.0) p.p. in the pre-crisis period. Figure 6.2 also shows that the access to internal finance was crucial to firm growth in times of recession: high (low) cash-flow, high-TFP firms grew 0.3 (0.4) p.p. more (less) in the crisis period compared with their counterparts in the pre-crisis, while the differences for labour productivity were 0.3 and −0.2, respectively. Moreover, during the recession, a high external dependency had a negative impact on employment growth. In fact, while in the pre-crisis period high-leveraged firms grew 0.2 p.p. faster than low-leveraged units, in both productivity measures, the effect was the opposite in the crisis, with high-leveraged firms growing slower, at around −0.1 and −0.2 p.p. in TFP and labour productivity, respectively.

Figure 6.2 **Estimated employment growth: productivity versus financial constraints**



Notes: The graphs show the estimated employment growth rates for constrained vs. unconstrained firms in the pre-crisis vs. crisis periods by productivity level, based on the estimations reported in Column 1 of Tables 6.3 and 6.5, assuming a sample mean for variables of no interest and a scenario of neutral *FD*, industry and year.

Overall, low-productivity firms had an increased risk of failure during the Great Recession and grew slower than their high-productivity counterparts, which is favourable to the cleansing hypothesis. Nevertheless, we also observe that financially constrained firms were more exposed to credit market restrictions. In fact, during the crisis, some firms shrunk or even exited, despite being more productive than others who survived and grew slowly, because they were financially constrained, which is a clear confirmation of the scarring hypothesis.

Chapter 7
Zombie firms: incidence, recovery and exit

Zombie firms are a prime example of misallocation of financial resources and distortion in firm selection. The resources sunk in zombie firms have risen over the last two decades, hampering productivity growth in developed economies (McGowan et al., 2018). The incidence of this phenomenon in Portugal, from 2005 to 2016, is described in this chapter, as well as the determinants that led firms to transition out of their zombie status by either recovering or exiting the market.

7.1. Zombie definition

The literature proposes different strategies to identify firms that could be flagged as zombies. Caballero et al. (2008), for example, define zombie firms as those receiving subsidised credit, that is, those whose actual interest rate paid is lower than the hypothetical risk-free interest rate (weighted by the firm debt structure). However, although zombie firms are conceptually associated with evergreen lending, this very aspect is ignored in the definition of Caballero et al. (2008). An identification of zombie firms that is only based on the subsidised credit criterion is particularly prone to two types of errors. First, healthy firms can be misclassified as zombies if they pay their interest below prime lending rates, given their low credit risk. Second, zombie firms can also be misclassified as non-zombies if they pay their interest at the rates prevailing in the market, as a result of evergreen loans (i.e., loans where the bank is rolling over the loan at the normal interest rate).

To overcome these shortcomings, two further aspects should be considered: profitability and evergreen lending (Fukuda and Nakamura, 2011). According to the former, firms whose operating income exceeds the hypothetical risk-free interest payment should not be classified as zombies, while, according to the latter, unprofitable highly leveraged firms with increasing external borrowings should be classified as zombies.

The method proposed by Caballero et al. (2008) cannot be replicated using our SCIE dataset. The main reason is that this method requires detailed information on the debt structure of each firm, which is not available. Note that the data in Caballero et al. (2008) and Fukuda and Nakamura (2011) is restricted to listed firms, which makes such information more easily available. Furthermore, our data does not allow us to observe actual interest payments on different forms of debt.

An alternative is to use interest coverage ratios. For example, McGowan et al. (2018) classify a firm as a zombie whenever: (i) it has an interest coverage ratio (i.e., the ratio of operating income to interest expenses) of less than one over three consecutive years; and (ii) it is more than ten years old. The three-year restriction is important to ensure that the zombie status is not driven by business cycle fluctuations. The age criterion allows for the distinction between zombie firms and young innovative start-ups. This procedure has, however, two major drawbacks in the context of our analysis. First, zombie firms are usually associated with "subsidised" interest payments. Moreover, when interest rates are very low for a long period, subsidised lending rates tend to be near zero (or even negative). As a result, in practice, it may be difficult to identify zombie firms through interest coverage ratios (Banerjee and Hoffmann, 2018). The second drawback is the change in accounting standards that took place in 2010, making the (total) interest expenses observable in the SCIE dataset only in the 2010–2017 interval.

The firm's characteristics can also be used to identify firms with persistent financial problems. Typically, these measures combine indicators of low profitability and high default risk. Schivardi et al. (2017), for example, propose the use of the following "profitability" and "default risk" criteria: (i) return-on-assets—measured as the three-year moving average of Earnings Before Interest, Taxes, Depreciation and Amortisation (EBITDA) over total assets—below the low-risk interest rate; and (ii) leverage (total financial debt over total assets) above the median in the low return-on-assets exiting group. Shen and Chen (2017) also define zombie firms as those who: (i) are capable of obtaining more debt; although they (ii) are already debt-ridden (leverage above 50%) and (iii) have no potential to repay that debt (i.e., with negative operating profits for three consecutive years). In turn, Storz et al. (2017) classify a firm as a zombie whenever for two consecutive years: (i) its return-on-assets (measured as net income over total assets) is negative; (ii) its net investment is negative, and (iii) its debt servicing capacity (measured as EBITDA over total financial debt) is lower than the median value.

Following Schivardi et al. (2017) and Carreira et al. (2020), we classify a firm as a zombie whenever: (i) its return-on-assets is lower than the low-risk interest rate at least for a period of three consecutive years; (ii) its leverage is higher than the industry-median (at the two-digit CAE Rev.3 level) of the low return-on-assets exiting group; (iii) it is more than five years old,[13] and (iv) it has more than three employees.[14] The rationale is that firms that are already debt-ridden and have no potential to repay their debt are likely to be on the verge of exit, unless their creditors sustain their continuation. The return-on-assets is defined as EBITDA over total assets. We compare return-on-assets to the annual average Euribor 12-month interest rate, the reference interest rate commonly used for loans by the Portuguese banking sector. The reason is that EBITDA is what is left of revenues to remunerate the capital after paying labour and intermediates inputs. The leverage is defined as the ratio of the sum of debt in current liabilities and long-term debt to total assets. We assume that the financial protection of zombie firms comes not only from banks forbearance but also from all types of creditors, a key issue in the Portuguese economy. In fact, on average, between 2010 and 2017, a quarter of the total debts observed in our dataset were owed to suppliers. In addition, according to the information provided by the "European Payment Industry" (INTRUM, 2018), late payment is a big issue in the Portuguese economy, and is especially relevant in "business to business" relationships, where the rates of "average contractual payment terms" and "average time taken to pay" are about 60 and 70 days, respectively, and the highest rates in Europe.

As in Nakamura (2017), we screen the zombie identification by excluding "one-shot zombie" firms from the zombie group, that is, one-off zombies or false zombies. Conversely, we include "one-shot restructuring" firms, that is, zombie firms that become non-zombies in $t+1$ and zombies again in $t+2$ (i.e., false restructurings).

We could have used other definitions of zombie firms. Table 7.1 shows that our definition of zombie firms is highly positively and significantly correlated with that of Shen and Chen (2017) and Schivardi et al. (2017), while the correlation with the definition of McGowan et al. (2018) is moderately positive. In turn, McGowan et al. (2018) have shown that their definition of zombie firms is positively and significantly correlated with that of Caballero at al. (2008). Moreover, our results proved robust using Shen and Chen (2017), Schivardi et al. (2017) and McGowan et al.'s (2018) definitions.[15]

Table 7.1 Tetrachoric correlation across four alternative definitions of zombie firms

Definition	[1]	[2]	[3]
[1] McGowan et al. (2018)	1		
[2] Shen and Chen (2017)	0.6753	1	
[3] Schivardi et al. (2017)	0.5990	0.8650	1
[4] Our own definition	0.6539	0.9135	0.9735

Note: The correlation coefficient is always statistically significant at the 0.01 level.

7.2. Incidence and characteristics of zombie firms

Zombie firms perform poorly not only with respect to productivity but also regarding real Gross Value Added (GVA) and EBITDA, as shown in Table 7.2. They also have higher debt than non-zombie firms. Furthermore, the Wilcoxon-Mann-Whitney test indicates that the mean and median of all main firm characteristics within the two groups are statistically different at the 1% significance level. This gap between zombie and non-zombie firms seems to have been even higher in the crisis period.

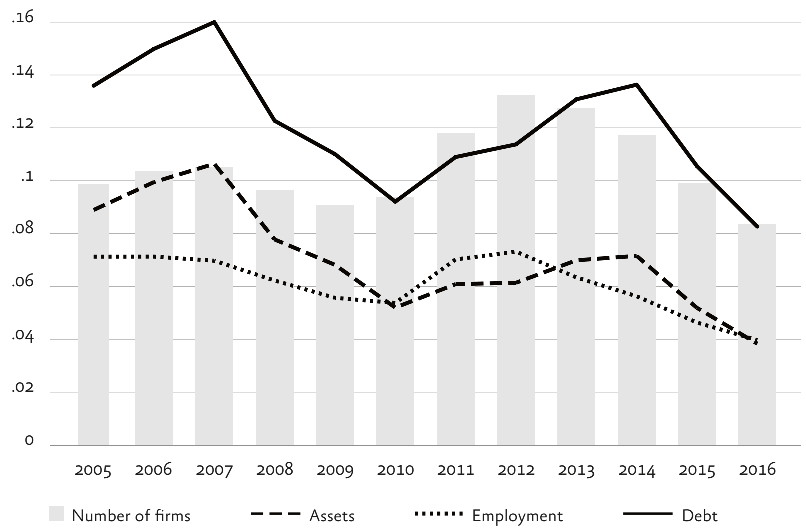
Table 7.2 Descriptive statistics of zombie and non-zombie firms

	2005–2016	2005–2007 Pre-crisis	2008–2013 Crisis	2014–2016 Recovery
a) *Non-zombie firms*				
TFP	0.04 (0.48)	0.04 (0.43)	0.05 (0.49)	0.04 (0.51)
Labour productivity	0.36 (2.87)	0.28 (2.39)	0.38 (2.98)	0.41 (3.07)
Number of employees	10.96 (19.40)	11.52 (19.74)	10.85 (19.22)	10.62 (19.38)
GVA	250.85 (594.99)	262.79 (598.85)	244.95 (588.02)	250.54 (604.96)
EBITDA	121.86 (1818.63)	131.32 (1936.42)	115.79 (1726.56)	124.49 (1875.39)
Assets	1109.83 (3112.46)	1045.02 (2916.70)	1136.20 (3168.21)	1123.25 (3192.64)
Debt	713.66 (2011.33)	707.11 (1935.25)	734.81 (2057.09)	677.00 (1993.31)
b) *Zombie firms*				
TFP	-0.37 (0.69)	-0.34 (0.62)	-0.37 (0.70)	-0.39 (0.75)
Labour productivity	-3.09 (5.68)	-2.49 (5.20)	-3.11 (5.72)	-3.69 (5.98)
Number of employees	6.99 (13.54)	8.22 (14.67)	6.98 (13.76)	5.67 (11.49)
GVA	63.94 (269.68)	94.39 (329.71)	60.35 (263.06)	39.36 (201.08)
EBITDA	-55.22 (542.66)	-34.82 (440.51)	-63.12 (584.87)	-59.19 (541.85)
Assets	787.56 (2666.58)	993.18 (2917.04)	787.88 (2678.27)	565.68 (2317.31)
Debt	849.94 (2231.79)	1008.27 (2401.59	849.09 (2244.58)	681.56 (1987.31)

Notes: Mean and standard deviation (in parenthesis). Total factor productivity (TFP) and labour productivity are the log deviation from the industry-year mean. The TFP is the log difference between output and the weighted sum of inputs. Labour productivity is the log of GVA per worker. GVA and EBITDA are the real Gross Value Added and Earnings Before Interest, Taxes, Depreciation and Amortisation, respectively. Assets and debt are the book value of total (net) assets and total debt. Monetary variables are in 10^3 Euros. All variables were winsorised at the 1^{st} and 99^{th} percentiles. Pooled yearly values.

Figure 7.1 shows the (unweighted) share of zombies in number of firms and according to three different (weighted) measures: debt, assets, and employment. As can be seen, zombie firms are quite present in the Portuguese economy. On average, about 11% of the firms in the sample were classified as zombies in 2005–2016, with a share of employment and assets sunk in zombie firms of 6% and 7%, respectively. Unsurprisingly, the share of zombie firms in total corporate debt, which is intended to capture the implied bad debt ratio, is larger than the share in terms of number of firms, at 12%, on average.[16]

Figure 7.1 Share of zombie firms, 2005-2016



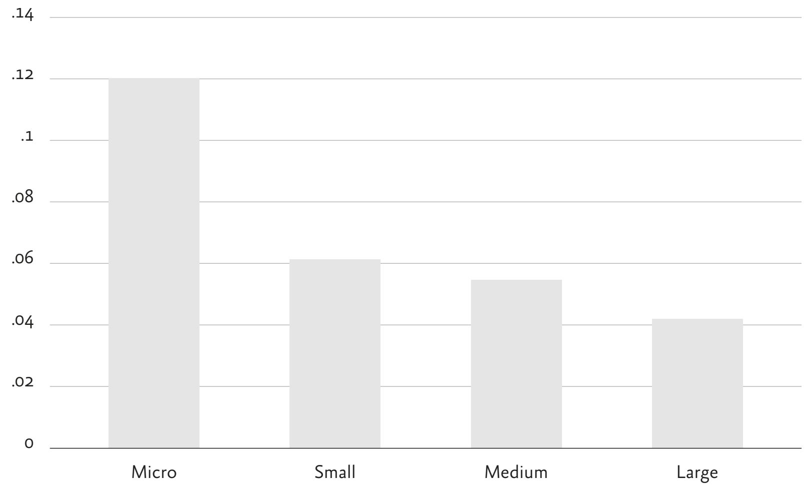
Notes: Zombie firms are defined as firms operating for more than five years with a return-on-assets below the low-risk interest rate over three consecutive years, and a leverage ratio above the industry median of the low return-on-assets exiting group. Assets, debt and employment refer to the share of zombie firms.

These shares broadly confirm the pattern observed in other European countries, as reported by McGowan et al. (2018) and Storz et al. (2017), for example. In particular, the shares of zombies (as a percentage of the total number of firms) in Figure 7.1 are similar to those reported by Storz et al. (2017) for Portugal, whose percentage values range from less than 8% in 2010 to 12% in 2013. They are higher than those found by Gouveia and Osterhold (2018) with an interest coverage ratio definition, whose estimates range from 6.5% in 2008 to 8.5% in 2013.

Noticeable cyclical fluctuations emerge in Figure 7.1. The share of zombies declines from 10.4% in 2006 to 9.1% in 2009, then it rises quickly to a peak in 2012, at 12.7%. This peak, which was also observed in Storz et al. (2017) and Gouveia and Osterhold (2018), corresponds to the austerity period, following the implementation of the 2011 Memorandum of Understanding. By 2016, the percentage of zombies declined to 8.4%.

One explanation for the difference between the unweighted and employment-weighted shares is that zombies tend to be smaller than non-zombies. As can be seen in Figure 7.2, the share of zombie firms is about 6 p.p. larger among micro-enterprises than among SMEs. We classify firms into a size category according to the number of employees (i.e., micro firms employ less than ten persons, small firms employ ten to 49 persons, medium firms employ 50 to 249 persons, and large firms employ 250 or more persons). Although large firms represent, on average, only 0.2% of the total of zombie firms, the share of employment and capital sunk in this size group is, on average, 14% and 10%, respectively (Table 7.3).

Figure 7.2 Share of zombie firms by size



Notes: According to Decree-Law 372/2007 the size class of a firm is defined by its number of employees. Micro-firms employ less than ten persons, small firms employ ten to 49 persons, medium firms employ 50 to 249 persons, and large firms employ 250 or more persons. Pooled yearly values, 2005–2016.

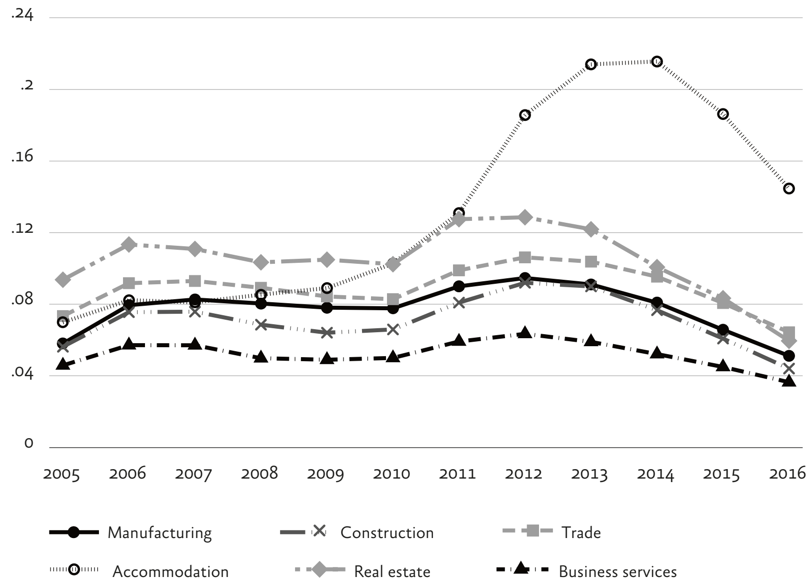
Table 7.3 Resources sunk in zombie firms by size and period (in percentage)

Size	2005–2016	Pre-crisis (2005–2007)	Crisis (2008–2013)	Recovery (2014–2016)
a) *Employment sunk*				
Micro	40.38	34.35	40.02	47.14
Small	27.99	30.76	28.44	24.30
Medium	18.12	17.44	19.20	16.64
Large	13.51	17.45	12.34	11.92
b) *Assets sunk*				
Micro	46.49	47.07	47.27	44.38
Small	26.56	31.92	24.97	24.39
Medium	16.60	15.16	16.84	17.56
Large	10.34	5.85	10.93	13.67

Notes: The table shows the distribution of labour and capital sunk in zombie firms by size category in different economic periods. The size categories are defined according to Decree-Law372/2007.

To investigate the incidence of zombie firms at the disaggregate level, Figure 7.3 depicts the corresponding shares by industry. While there are some differences across industries, the general pattern holds. The exception is the accommodation and food services sector, where the percentage of zombie firms rose sharply from 7.0% in 2005 to 21.6% in 2014, with a sizeable increase of 14.6 p.p. It appears that during bad times non-performing firms in this industry are relatively more exposed to personal costs associated with failed entrepreneurship and barriers to restructuring, which unreasonably foster the survival of firms that would otherwise exit the market.[17] On average, the other sectors exhibit values in a range of 5.2% (business services) to 13.8% (real estate).

Figure 7.3 Share of zombie firms by industry, 2005-2016



Note: See Table 7.1 notes.

7.3. Industry productivity and the share of zombie firms

As discussed in Chapter 2, zombie firms tend to hinder competition and the efficient allocation of resources, thus generating lower (aggregate) productivity growth. Figure 7.4 examines the correlation between the ratio of zombie firms and the (weighted) aggregate productivity at the industry-year level. As can be seen, a negative relationship emerges, whereby a higher share of zombies in an industry is associated with a below-average industry productivity performance. More precisely, a 1% decline in the share of zombie firms entails a 0.5% (3.1%) rise in the level of industry TFP (labour productivity).

Figure 7.4 Correlation between industry productivity and the share of zombie firms

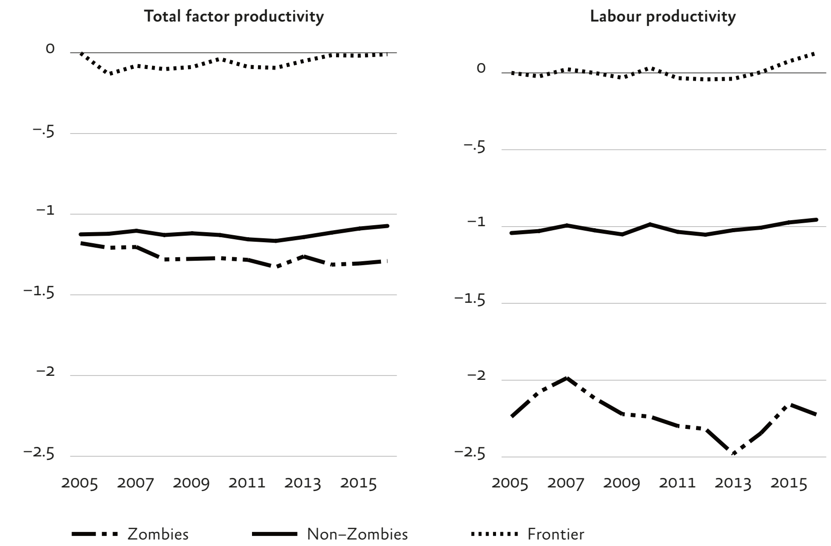
Notes: Each dot reports industry productivity and the share of zombies at the industry-year level and at the two-digit NACE Rev.2 level (2005–2016). Industry total factor productivity (TFP) and industry labour productivity are defined as the log deviation from the year mean.

In a well-functioning market economy, the Schumpeterian "creative destruction" forces poorly performing firms to restructure or exit the market. Consequently, the productivity gap between frontier and zombie firms is expected to narrow rather than widen, by eliminating the presumable worst-performing zombies. However, rather than showing zombie firms catching-up with the technological frontier, Figure 7.5 shows a persistent and widening productivity gap. (The technological frontier is given by the firms at the top 5% in terms of productivity, each year, and within each industry.) Specifically, zombie firms have become relatively less productive, with their TFP decreasing at an average annual rate of 1.0%, compared with the TFP gains of 0.5% per annum for non-zombie firms, which results in a divergence of the productivity gap of 1.5 p.p. per annum. This divergence process is less pronounced in labour productivity, at 0.7 p.p. The productivity gap between frontier and zombie firms also tends to widen during this period, at 0.9 and 1.0 p.p. per annum, on average, in TFP and labour productivity, respectively.

7.4. The dynamics of zombie firms

In a well-functioning market economy, poorly performing firms should be compelled to restructure or exit. However, forbearance lending by banks and other creditors may allow zombie firms to continue in such status over time. On average, 74% of zombie firms remained zombies two years after being flagged, and a quarter of these firms were still alive as zombies by the end of the fourth year (Table 7.4). Moreover, firms flagged as zombies during the period of crisis (2008–2013) were more likely to stay in this status than those who became zombies before the crisis. In any case, the likelihood of remaining a zombie is high, which indicates the presence of significant barriers to exiting or restructuring.

Figure 7.5 Productivity gap across frontier, zombie and non-zombie firms



Notes: *Zombies* and *non-zombies* lines give the average (log) productivity weighted by firm output for TFP, and by firm employment for labour productivity within each (two-digit) industry. The global *frontier* is defined as the average (log) productivity of the 5% most productive firms within each industry. Unweighted averages across industries were normalised to 0 for the frontier in the starting year.

Table 7.5 shows the recovery and exit rates of zombie firms. The recovery (exit) rate corresponds to the fraction of zombie firms in *t* that recovered (exited) in *t*+1. The recovery and exit rates are relatively low, which means that the rate of firms that "remain as a zombie" is fairly high. Moreover, the exit rate increased to maximum values during the crisis, while the recovery rate dropped. These two aspects, and the possible fall of new zombies, explain the rise in the share of zombie firms observed during the crisis. The recovery rate in the post-crisis period, in turn, was higher than that of the crisis and the pre-crisis periods. Finally, the general pattern holds across industries with small differences in the selected rates.

Table 7.4 Survival rates of zombie firms by year-cohort (in percentage)

Cohort	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2005	100	66.3	43.3	27.0	16.9	10.2	8.0	5.8	4.1	3.1	2.3	1.7
2006		100	79.8	42.2	22.5	13.5	9.7	6.8	4.9	3.5	2.6	1.9
2007			100	75.0	37.3	19.7	13.7	9.6	6.8	4.7	3.2	2.3
2008				100	71.4	35.5	23.6	15.7	10.6	7.6	5.6	4.2
2009					100	69.8	45.0	27.6	17.4	11.5	8.2	6.0
2010						100	80.7	46.1	28.2	17.7	11.5	7.7
2011							100	79.1	43.6	27.2	17.1	11.5
2012								100	72.9	41.1	24.6	15.4
2013									100	72.9	40.0	23.1
2014										100	70.6	36.6
2015											100	71.1

Notes: The figures in each row (cohort) report how firms flagged as zombies in a certain year survive over time. They were computed as the ratio of the number of remaining zombie firms to the number of zombie firms in the year in which they became zombies. Unweighted averages across industries.

Table 7.5 Recovery and exit rate of zombie firms by sector and period (in percentage)

	Recovery rate			Exit rate		
	Pre-crisis (2005–2007)	Crisis (2008–2013)	Recovery (2014–2016)	Pre-crisis (2005–2007)	Crisis (2008–2013)	Recovery (2014–2016)
Manufacturing	10.0	9.7	16.0	14.8	17.5	15.4
Construction	14.6	10.9	18.2	12.2	20.5	18.7
Trade	10.5	9.3	14.3	11.9	16.0	15.1
Accommodation	11.9	6.3	14.3	10.1	10.9	10.9
Real estate	14.7	13.2	19.3	7.9	14.2	13.0
Business services	14.7	13.9	15.8	10.9	15.3	16.5
Average	12.7	10.6	16.3	11.3	15.7	14.9

Notes: The recovery (exit) rate of zombies is defined as the ratio of zombies that recover (exit) in t+1 to the total number of zombie firms in t. Unweighted averages across industries.

Zombie firms require approximately three years and six months to exit and three years and two months to recover. In Table 7.6, we compute the fraction of zombie firms in year t–3 that remain zombies in t, and the corresponding fraction of those that restructure or die between t–3 and t. On average, about 26% of the zombie firms remained zombies after three years, while over 46% restructured and 28% exited within the same timeframe.

Table 7.6 Transition rates (in percentage)

	Transition rates in t		
	Zombie	Recovery	Exit
Zombie at t–3	25.5	46.4	28.1

Notes: Table 7.6 shows the transition rates between years t–3 and t, with t = 2008, 2011, 2014 and 2017. Unweighted averages across industries.

7.5. The determinants of recovery and exit of zombie firms

We now investigate the determinants of zombie firm transitions into different destinations within a multinomial logistic model approach. In each period, a zombie firm can either remain as a zombie, recover or exit the market (coded as 1, 2 and 3, respectively). Formally, assuming that the extreme value distributed error terms are independent and identically distributed, the probability that the outcome for the individual i in year t is destination j (j = 1, 2, 3), conditional on a vector of variables $X_{i(t-1)}$, is given by:

$$p_{itj} = \Pr(Y_{it} = j) = \exp(X'_{i(t-1)}\,\beta_j) / \textstyle\sum_{l=1}^{3} \exp(X'_{i(t-1)}\beta_l). \qquad (7.1)$$

In this setting, the explanatory variables $X_{i(t-1)}$ are lagged one year to avoid the simultaneous bias problem (Fukuda and Nakamura, 2011).

The vector $X_{i(t-1)}$ includes three subsets of explanatory variables. The first subset of covariates attempts to proxy the operational restructuring of zombie firms and contains the *Change in the number of employees*, the *Change in assets*, and the *Change in productivity* (i.e., *ΔLog Labour*, *ΔLog Assets*, *ΔLog (labour and total factor) productivity*, respectively), all computed as the logarithmic difference between two consecutive years (see Chapter 3 for a definition of all explanatory variables). Since downsizing and restructuring are the typical strategies adopted by troubled firms, a negative sign for the first two variables and a positive sign for the third variable are expected in the transition into a state of recovery. The other way around is possibly true when exiting the market, although downsizing may also flag the presence of the *shadow of death* effect, in which case a negative sign is expected (Carreira and Teixeira, 2011).

The second subset of covariates comprises the financial variables that are related to external and internal resources and captures the financial restructuring capacity of the firms. It includes the *Leverage ratio* and the *Return-on-assets*. Zombie firms with a higher external debt are more difficult to restructure and face a higher risk of death. Financial restructuring involves a reduction in the debt of a firm and a significant modification in its structure. The leverage ratio only decreases if the debt reduction is greater than the expected reduction in total assets. It is expected that the leverage ratio has a negative (positive) impact on the probability of recovery (exit). Therefore, firms with higher revenues should face less severe financial constraints in the future. Consequently, the return-on-assets variable should have a positive (negative) effect on the probability of recovery (exit).

Finally, we include four firm-level control variables: *Zombie duration*, firm *Age*, *Employment*, and *Assets*. We also included industry and year dummies in the regression to capture the external environment. The restructuring of firms who went through long periods of economic and financial trouble is rather challenging. However, this interval can also be interpreted as the time required to implement a restructuring strategy. It is expected that zombie firms recover or exit the market over time since the only factors that allow these firms to remain zombies for a long time are forbearance lending by banks and other creditors. The effect of (employment and assets) size and age on the recovery of a firm can also be twofold. On the one hand, larger and older firms have more resources and management capabilities to restructure. On the other hand, due to the presence of vested interests, inertia tends to be higher, making these firms increasingly ill-suited to deal with a changing environment. Therefore, although their effects should be controlled for, either sign is expected for these variables.

Tables 7.7 and 7.8 present the descriptive statistics and the correlation matrix of covariates, respectively.

Table 7.7 **Descriptive statistics of covariates**

Variables	Remaining zombie	Recovery	Exit
ΔLog *Labour*	-0.082 (0.404)	-0.080 (0.408)	-0.273 (0.580)
ΔLog *Assets*	-0.099 (0.415)	-0.079 (0.442)	-0.467 (0.823)
ΔLog *TFP*	-0.129 (0.557)	-0.014 (0.563)	-0.255 (0.919)
ΔLog *Labour productivity*	-1.444 (7.538)	-0.320 (7.083)	-3.404 (9.033)
Log *Leverage*	0.556 (0.649)	0.392 (0.550)	0.845 (0.788)
Log *Return-on-assets*	-8.727 (1.464)	-8.418 (1.827)	-8.995 (0.968)
Log *Zombie duration*	0.650 (0.658)	0.648 (0.569)	0.826 (0.585)
Log *Employment*	1.405 (0.877)	1.467 (0.908)	1.146 (0.985)
Log *Assets*	11.874 (1.665)	12.077 (1.680)	11.483 (1.833)
Log *Age*	2.523 (0.510)	2.497 (0.501)	2.385 (0.325)

Notes: Mean values and standard deviations (in parentheses). The variables are defined in the text and were winsorised at the 1st and 99th percentiles. Pooled yearly values, 2005–2016.

Table 7.9 presents the results of the multinomial logit regression for TFP and labour productivity. In both specifications, the null hypothesis that all coefficients are jointly equal to zero is rejected at the 0.01 level of significance (see the Wald test at the bottom of the table). Given the reference category, the sign of each coefficient can be interpreted as the effectiveness of each explanatory variable in the probability of transitioning into recovery or exit.

Table 7.8 **Correlation across covariates**

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
[1] Zombie dummy status	1									
[2] ΔLog Labour	-0.119	1								
[3] ΔLog *Assets*	-0.194	0.155	1							
[4] ΔLog *TFP*	-0.027	-0.005	-0.039	1						
[5] ΔLog *Labour prod.*	-0.047	0.089	0.145	0.591	1					
[6] Log *Leverage*	0.081	-0.039	-0.329	0.072	-0.015	1				
[7] Log *Return-on-assets*	-0.017	0.037	0.156	0.100	0.117	-0.247	1			
[8] Log *Zombie duration*	0.074	-0.039	0.017	0.126	0.097	0.343	-0.080	1		
[9] Log *Employment*	-0.068	0.261	0.059	0.023	0.050	-0.168	0.064	-0.168	1	
[10] Log *Assets*	-0.045	-0.024	0.278	-0.060	0.004	-0.620	0.257	-0.089	0.419	1
[11] Log *Age*	-0.087	0.022	-0.003	0.037	0.028	0.067	-0.119	0.296	-0.010	-0.030

Note: See Table 7.7 notes.

The *Change in assets* coefficient in the recovery category for both models (Columns 1 and 3) is significantly negative, as expected. In particular, all else constant, a one-unit decrease in *ΔLog Assets* (assumed as a consequence of a restructuring process) increases the relative odds of recovery in 5.3 (10.2) compared with remaining as a zombie.[18] The coefficient on the *Change in the number of employees* variable is only significantly negative in labour productivity. In the case of exit, the coefficients *Change in assets* and *Change in the number of employees* are both negative: the odds ratio of *ΔLog Assets* (*ΔLog Labour*) decreases by 64.8 and 62.3% (38.9 and 37.9%) in TFP and labour productivity, respectively. In this case, we may have the presence of the shadow of death effect or simply the effect of unsuccessful restructuring. In any event, what is certain is that the probability of a firm remaining a zombie decreases with downsizing.

Table 7.9 **Determinants of recovery and exit of zombie firms**

	TFP		Labour productivity	
	Recovery	Exit	Recovery	Exit
Variables	(1)	(2)	(3)	(4)
ΔLog *Assets*	-0.054*** (0.017)	-1.043*** (0.017)	-0.108*** (0.017)	-0.976*** (0.017)
ΔLog *Labour*	-0.018 (0.017)	-0.492*** (0.019)	-0.067*** (0.016)	-0.476*** (0.019)
ΔLog *Productivity*	0.376*** (0.012)	-0.331*** (0.013)	0.019*** (0.001)	-0.016*** (0.001)
Log *Leverage*	-0.620*** (0.016)	0.242*** (0.016)	-0.611*** (0.016)	0.243*** (0.016)
Log *Return-on-assets*	0.062*** (0.004)	-0.095*** (0.007)	0.070*** (0.004)	-0.108*** (0.007)
Log *Zombie duration*	0.222*** (0.013)	0.691*** (0.014)	0.248*** (0.013)	0.666*** 0.014)
Log *Age*	-0.019 (0.015)	-1.211*** (0.021)	-0.020 (0.015)	-1.201*** (0.020)
Log *Employment*	0.113*** (0.008)	-0.164*** (0.011)	0.114*** (0.008)	-0.182*** (0.011)
Log *Assets*	-0.106*** (0.005)	0.049*** (0.007)	-0.108*** (0.005)	0.058*** (0.007)
No. of observations		195,155		195,155
Wald chi-square		5538154***		5927285***
Log pseudolikelihood		-149767		-150578
Pseudo R^2		0.1011		0.0962

Notes: Multinomial logit model. Columns 1 to 4 report the coefficients' estimates. The base category for the dependent variable is remaining in the zombie status. The variables were winsorised at the 1st and 99th percentiles. Regressions include industry dummies, year dummies and a constant term. Firm-cluster robust standard errors are given in parentheses. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

As expected, the coefficient on the *Change in productivity* is positive in Columns 1 and 3, and negative in Columns 2 and 4. For example, *ΔLog TFP* has an odds ratio of 1.456, suggesting that a one-unit increase in the TFP change makes the outcome of recovery 45.6% more likely, all else constant. In turn, the relative risk of exit compared with remaining a zombie decreases by 28.2%. In short, technological restructuring seems to be an effective way to promote the recovery of troubled firms, and also reduce their likelihood of exit.

Regarding the financial restructuring capacity, as expected, the *Log Leverage* (*Log Return-on-assets*) coefficients are significantly negative (positive) in Columns 1 and 3 and, conversely, in Columns 2 and 4. For example, in the case of the TFP, a one-unit increase in leverage reduces the relative odds of recovery in 46.2%; and a one-unit increase in return-on-assets increases those relative odds by 6.4%. Firms that reduce their debt at a faster rate than the (expected) asset reduction are more likely to recover and less likely to exit. By contrast, rising revenues are associated with a higher probability of recovery and a lower probability of exiting the market.

The *Zombie duration* coefficient is significantly positive in all columns. In particular, the relative odds ratio of recovery compared with remaining a zombie is 1.217, while the respective odds ratio in the case of exit is 2.051. This means that firms are less likely to remain zombies, an expected effect considering that most zombies only stay alive due to forbearance lending by banks and other creditors, and that information asymmetry decreases over time.

The effect of firm size is less straightforward. Measured in number of employees, the larger the firm, the higher (lower) its likelihood of transitioning into recovery (exit). Conversely, the *Log Assets* variable coefficient is significantly negative in the case of recovery, and positive in the case of exit. The fact that the firm age coefficient is positive (negative), suggests that transitions into recovery (exit) are more (less) likely for older firms. Apparently, larger (measured in number of employees) and older firms have more resources and management capabilities to restructure. The managers of these firms also have a substantial power to turn the tables on hostile creditors because of the adverse consequences of their failure for creditors, and perhaps the whole financial system (*vulgo*: "too big to fail"; Moosa, 2010).[19]

Chapter 8
Assessing the 2012 reform of the insolvency regime

As seen in Chapter 2, a well-functioning business environment can promote productivity growth by reducing distortions in product and input markets. Efficient insolvency and proper enforcement have that potential too. In this chapter, we carry out an economic evaluation of the insolvency regime reforms implemented in Portugal in 2012, analysing the particular case of financially distressed companies, specifically zombie firms.

8.1. The insolvency regime reforms

The 2004 Insolvency and Company Recovery Code (CIRE) was designed to prioritise the protection of creditors' rights, favouring liquidation over corporate restructuring. As of 2012, the Portuguese authorities carried out reforms in CIRE to generate a new orientation, with an emphasis on business reorganisation through the solidification of the pre-insolvency regime. Specifically, the 2012 reforms included: (i) a hybrid pre-insolvency mechanism (with judicial supervision) called "Special Revitalisation Process" (PER), intended to promote a fast restructuring agreement between debtors and creditors in firms that are in an imminent insolvency situation; (ii) priority for creditors who inject new capital for restructuring if the company is subsequently liquidated, (that is, if the reorganisation fails); and (iii) an out-of-court recovery mechanism (SIREVE) focused mainly on SMEs and on the technical support of the Portuguese Agency for Competition and Innovation (IAPMEI).

Early warning mechanisms were also created in subsequent years. Specifically, in 2014 the Bank of Portugal developed a mechanism for credit institutions to detect companies at "risk of default", while in 2015 the IAPMEI created a financial self-assessment tool for firms.

The entire set of measures sought timely insolvency statements and resolved conflicts in an agile and efficient manner, while at the same time protecting the rights of both creditors and debtors in a balanced way. According to the OECD study conducted by McGowan and Andrews (2018), comparing the legislation in force in 2010 to the legislation in force in 2016, Portugal was classified as one of the countries who carried out more extensive reforms in its insolvency regulation, and the country among the four analysed OECD countries with the most efficient regimes. Portugal was also considered one of the most efficient countries in regulatory terms, in the pre-insolvency regime, seconded only by the U.K, with the main improvement being in the area of the "facility/availability of preventive measures" (Carcea et al., 2015).

Nonetheless, McGowan and Andrews (2018) note that the reform that allowed new financing during the restructuring process was not entirely efficient, since the priority given to new creditors was placed above all previous creditors and not just over the unsecured ones. This is contrary to the OECD's recommendations, as it generates adverse effects on credit availability and legal certainty. The authors also argue that although the Portuguese regime distinguishes between honest and fraudulent bankruptcies, the discharge of failed entrepreneurs is slow. On the whole, bankruptcy may be a very costly event, with hostile effects on timely insolvencies and future entrepreneurship (Armour and Cumming, 2008; McGowan and Andrews, 2018).

While between 2007 and 2012 the number of "bankruptcy, insolvency and recovery" processes amounted to 14,010, in 2013-2018, the number increased to 25,661 cases, of which 3,310 were related to PER procedures. Moreover, as of the entry into force of the SIREVE until 2018, 632 companies (98% of which SMEs) benefited from this out-of-court recovery mechanism, with 43% reaching an agreement in seven months, on average.[20] Seemingly, these official figures offer us a preliminary description of the evolution of the main procedures, as well as an immediate measure of the impact of the implemented policy changes.

8.2. Assessment methodology

Our empirical approach aims to investigate whether the implemented institutional reforms were effective in reducing reallocation barriers, that is, whether the reforms have strengthened business dynamism and market selection through (i) a reduction in the zombie entrenchment (i.e., the lifetime of firms in a zombie status), mirrored on (ii) a greater likelihood of recovery for financially distressed but viable firms and (iii) a higher exit probability of 'true' zombies. We also examine the impact of reforms on productivity dispersion. We apply survival analysis and multinomial logistic regression models to study the effect of the reforms using a non-linear diff-in-diff approach (after Karaca-Mandic et al., 2012). We will be looking, in particular, at the role of the size of a firm on insolvency, and the associated ownership and debt structures.

To analyse the effect of reforms on the probability of survival as zombie, we will, again, deploy the semi-parametric Cox Proportional Hazard model, noting that the failure event corresponds to recovering or exiting the market:

$$h_i(t) = \mathrm{h}_0(t) * \exp\{\vartheta_0 * IR_t + \boldsymbol{D}'_{it}\boldsymbol{\Lambda} + [\boldsymbol{D}'_{it}\boldsymbol{\Theta}] * IR_t + \boldsymbol{X}'_{it}\boldsymbol{\Omega}\}, \tag{8.1}$$

where $\boldsymbol{D}$ is the vector of the key explanatory variables, namely *capital*, *labour* (i.e., number of employees) and *leverage*; $\boldsymbol{X}$ contains the control variables *TFP*, *operating cash-flow*, firm *age*, annual growth rate of GDP by region (NUTS II regions), and industry and location dummies, all in logarithms except the GDP growth rate and the dummies (see Chapter 3 for a definition of all explanatory variables). The model also contains the (interaction) IR_t dummy variable that takes the value of one if the year is greater than 2012 (i.e., after the reforms). We are particularly interested in analysing the effect of reforms on the probability of firms exiting their zombie status, as well as the effect of these reforms on the relationship between the capital, labour and leverage covariates and the hazard function, using the corresponding interaction terms.

Given that the dependent variable is the hazard rate, a negative (positive) coefficient implies that the corresponding variable reduces (increases) the firms' instantaneous probability of exiting their zombie status, which increases (decreases) their chances of survival. We, therefore, expect a negative sign of the capital and labour coefficients for two reasons. Firstly, because the larger the company, the more difficult it is to resolve insolvency conflicts due to the higher complexity of its ownership and debt structures. Secondly, since smaller firms depend mainly on (a few) banks whose debt is mostly secured, the smaller the company, the greater the likelihood of being liquidated in an insolvency event and, thus, exiting its zombie status. In both cases, we have an inverse relationship. However, considering that the reforms attempt to facilitate reorganisation agreements, we expect a positive sign in the corresponding interaction terms.

Regarding leverage, although a high level of relative indebtedness is likely to increase the time needed to resolve insolvency conflicts, it is expected that the higher the leverage ratio, the higher the likelihood of exit (i.e., we expect a positive sign). Nonetheless, since the reforms encourage both a new financial injection to foster the reorganisation of viable businesses and less bank forbearance, we expect a positive interaction term. In other words, if the reforms are effective, recovery and exit should increase.

Finally, if the reforms reduce zombie entrenchment, the IR coefficient should be positive, given the presumption that they reduce the likelihood of zombie survival (more rapid exit and/or recovery).

We proceed to investigate the determinants of zombie transition with a twofold objective. First, we seek to examine whether the reforms are efficient in strengthening the within-zombie selection, by boosting the recovery of the most productive firms and the exit of the least productive ones. Second, we want to ascertain whether the changes in zombie entrenchment take place due to changes in the likelihood of recovery, exit, or both. For this purpose, we apply the multinomial logistic model in which the base category is defined as "remaining as a zombie" (coded as 1; and recovery and exit are coded as 2 and 3, respectively):

$$p_{itj} = \Pr(Y_{it} = j) = \frac{\exp\{c_j + \psi_{0j} * IR_t + \boldsymbol{D}'_{i(t-1)})\, \Phi_j + [\boldsymbol{D}'_{i(t-1)}\Psi_j] * IR_t + \boldsymbol{X}'_{i(t-!)} Z_j\}}{\sum^3_{l=1} \exp\{c_j + \psi_{0j} * IR_t + \boldsymbol{D}'_{i(t-1)})\, \Phi_j + [\boldsymbol{D}'_{i(t-1)}\Psi_j] * IR_t + \boldsymbol{X}'_{i(t-!)} Z_j\}}\,. \quad (8.2)$$

The set of variables is the same as the previous CPH model (8.1), and the explanatory variables are lagged one period to avoid the endogeneity generated by the simultaneity bias.

We interpret the effects of the key explanatory variables, as well as the interaction effects, on the likelihood of each transition in this nonlinear model context, by computing average marginal effects, AME (Karaca-Mandic et al., 2012).[21] Given that we have three transition categories, we obtain three marginal effects for each regressor: $\text{AME}_{j,\kappa,\tau}$, where the subscript τ denotes the period of time, with $\tau = 0, 1, 2$ indicating the ex-ante, ex-post, and the entire sample period, respectively; and κ denotes the explanatory variable. The marginal effects of each regressor add up to zero because probabilities add up to one. This property conveniently allows us to examine which effect prevails. While the marginal effects for the entire interval allow us to analyse the one-unit change in κ on the probability that the destination j is the outcome in t+1, the pairwise comparison of marginal effects "before" and "after" allow us to analyse the effects of the reforms on these relationships. For instance, if $\text{AME}_{j,\kappa,1}$ and $\text{AME}_{j,\kappa,0}$ have the same sign but the former is larger than the latter, the corresponding relationship is strengthened after the reform.

It is expected that the most productive zombies have higher probabilities of recovering, while the least productive have higher probabilities of exiting the market. Moreover, it is anticipated that the reforms will strengthen this selection process. Therefore, we expect that $AME_{2,TFP,1} > AME_{2,TFP,0} > 0$ and $AME_{3,TFP,1} < AME_{3,TFP,0} < 0$. If $AME_{2,TFP,1} - AME_{2,TFP,0}$ is negative. This implies that the reforms made recovery less likely despite an increase in productivity, which, in turn, means that the reforms impose greater barriers to the restructuring of viable companies. On the other hand, if $AME_{3,TFP,1} - AME_{3,TFP,0}$ is positive, then the increase in productivity in the post-reforms period is associated with a higher probability of exit, which implies that relatively more productive firms may be inefficiently liquidated.

Regarding firm size, proxied by capital and labour, in the survival analysis we hypothesised that the larger the company, the greater the probability of remaining as a zombie. However, as discussed in Section 2.4, Chapter 2, the effect of firm size may be ambiguous. Due to the complexity of the ownership and debt structures of larger firms, we may expect a negative relationship between size and the probability of recovery and exit, compared with remaining as a zombie. Additionally, regarding the exit probability, since smaller companies are more likely to be liquidated due to a higher share of concentrated and secured debt, the negative relationship between firm size and exit probability is reinforced. However, since larger firms often command more resources and have more managerial capabilities, they are expected to have a higher probability of recovery and a lower risk of exit. On the other hand, it is expected that the reforms increase the likelihood of recovery *and* exit, somehow reversing the effect of size on both events. Thus, we expect $AME_{2,Capital(Labour),1} > AME_{2,Capital(Labour),0}$ and $AME_{3,Capital(Labour),1} > AME_{3,Capital(Labour),0}$.

Financially distressed firms are less likely to recover and are at a higher risk of exiting the market. We, therefore, expect that leverage has a negative (positive) effect on the probability of recovery (exit). Nonetheless, if the incentive to inject new financing into the reorganisation of viable businesses is effective, this should result in healthier leverage ratios that increase the chances of recovery. In this case, we expect $AME_{2,Leverge,1} - AME_{2,Leverge,0}$ to be positive, thus diminishing the negative effect of leverage on recovery. That is: debt has to be reduced faster than assets or assets have to grow faster than debt; otherwise, the new financing (or debt restructuring) would be worsening, rather than improving the firm's financial conditions. Regarding the exit probability, the lower banking forbearance should further reduce the survival chances of zombies with high leverage levels. Hence, we expect a positive sign in $AME_{3,Leverge,1} - AME_{3,Leverge,0}$. Finally, since the reforms aim to facilitate the recovery of viable firms that are temporarily financially distressed, as well as the exit of unviable firms, we expect the difference in the expected probabilities 'before' and 'after' to be positive in both cases.

8.3. The effect of reforms on zombie entrenchment

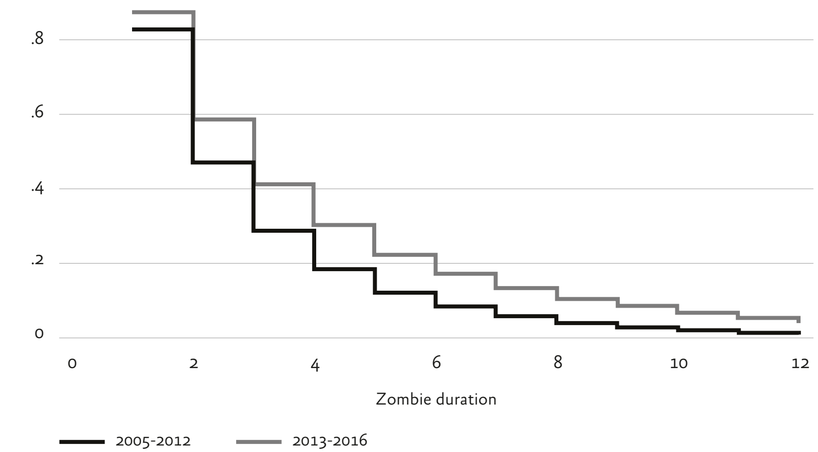
Table 8.1 presents the results of the CPH model, contrasting the results *before* and *after* the reforms implemented in 2012. As expected, we observe that the larger the firm (in terms of capital and employment), the lower the hazard rate (i.e., the likelihood of recovery or exit). The estimations also show that a higher level of financial leverage is associated with a greater hazard rate. Furthermore, there is strong evidence that the zombie survival probability is lower in the post-reforms period, as shown by the positive and highly significant coefficients associated with the *IR* dummy. As shown in Column 2, the hazard rate of zombies in the post-reforms period (i.e., for *IR*=1) is 1.410 times higher than it was before the introduction of the reforms. As shown in Figure 8.1, after the reforms, there was also a clear downward shift in the zombie survival function, conditional on Cox-regression estimates. We interpret this result as evidence in favour of a decline in reallocation barriers.

Table 8.1 The effect of the 2012 reforms on zombie entrenchment-time

Variables	(1)	(2)	(3)
IR		0.3435*** (0.0100)	0.4840*** (0.0870)
Capital	−0.0570*** (0.0040)	−0.0523*** (0.0040)	−0.0486*** (0.0049)
Capital × IR			−0.0061 (0.0072)
Labour	−0.0546*** (0.0060)	−0.0399*** (0.0060)	−0.0609*** (0.0073)
Labour × IR			0.0616*** (0.0112)
Leverage	0.1879*** (0.0079)	0.1753*** (0.0079)	0.2636*** (0.0100)
Leverage × IR			−0.1879*** (0.0138)
Observations	198,104	198,104	198,104
Wald test	5305.16	6362.11	6754.10
Log-likelihood	-543518.98	-542970.28	-542783.98

Notes: The Cox proportional hazard regression with 'ties' was handled with the Efron method. The dependent variable is the (instantaneous) probability of exiting the zombie status. Capital, Labour and Leverage are in logs. IR is a dummy for the post-reforms period. Regressions include the following (unreported) control variables: log of TFP, log of cash-flow, log of age, business cycle measure (GDP-growth rate by region), and industry and location dummies. The variables were winsorised at the 1st and 99th percentiles. Firm-cluster robust standard errors are given in parenthesis. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Figure 8.1 Conditional survival function of zombies before and after the reforms



Notes: The graph shows the estimated survival function of zombies, before and after the reforms, conditional on the Cox-regression estimates. The survival function reports the probability of remaining as a zombie beyond *t*.

Column 3 of Table 8.1 shows the model specification with the IR interaction terms to assess how the relationship between entrenchment and the key covariates differs *before* and *after* the reforms. The results are, however, less straightforward. First, the *IR-Capital* interaction term is negative, but not statistically significant, while the *IR-Employment* interaction is positive and highly statistically significant. Thus, it seems that the reduction in the positive relationship between size and zombie entrenchment primarily arises through the effect on employment rather than on capital. Specifically, while in the pre-reforms period a one-point increase in (log) employment reduced the hazard rate by 5.9%, the same marginal change in the post-reforms period rose the hazard by 0.7%, all else constant. That is, the reforms decreased the probability of survival, associated with a one-unit increase in employment, by 6.0%.

Second, although a positive sign is expected in the *IR-Leverage* interaction, the corresponding coefficient is actually negative and statistically significant at the 1% level, which indicates an attenuation in the effect of leverage on the zombies' hazard rate after the reforms. Indeed, while in the pre-reforms period a one-unit increase in (log) leverage rose the hazard by 30.2%, in the post-reforms period this change only generated an increase of 7.9%, all else constant. An open question is then whether the negative effect of the interaction is due to a lower probability of recovery, exit, or both. We address this issue in the multinomial analysis in the next section.

8.4. The effect of reforms on zombie recovery and exit

Table 8.2 shows the main post-estimation results obtained from the multinomial regression model. In particular, the expected probabilities for each transition, the average marginal effects, and the interaction effects. The model's predictions for the entire sample period show that the likelihood of a firm remaining as a zombie is approximately 73%, which is about five to six times higher than in the other two alternative transitions (i.e., recovery and exit). However, the interesting finding is that the entrenchment of a typical zombie has decreased after the reforms. In effect, the "remain as a zombie" probability is 75.0% for *IR*=0 and 66.9% for *IR*=1, that is, a decrease of 8.1 p.p. The reduction in the "remain as a zombie" likelihood is mostly explained by an increase of 6.1 p.p. in the recovery probability, while the increase in the exit likelihood does not exceed 2.0 p.p.

As expected, the more (less) productive the zombies, the more likely they are to recover (exit) instead of remaining in their default status (as a zombie). Moreover, as shown in the last column of the table (pairwise comparisons), the difference in marginal effects of TFP upon conditional recovery likelihood (before and after the reforms) is highly statistically significant and positive at 2.7 p.p. This means that after the reforms the most productive zombies are even more likely to recover. In the case of exit, contrary to the hypothesised, the difference in AMEs is significantly positive. In fact, although a one-unit change in TFP in the post-reforms period is still associated with a decrease of 6.4% in the probability of exit, this decrease is smaller than the corresponding one in the pre-reforms period, at 7.4%. Since the non-transition is the base category, the results of the pairwise comparison show that the least productive zombies became 1.0 p.p. less (more) likely to exit (remain as a zombie). Thus, the estimates indicate that the within-zombie selection at the exit margin has decreased or that potentially viable firms were inefficiently liquidated after the reforms.[22]

Table 8.2 **Estimated probabilities, average marginal effects and differences-in-differences between pre and post-reforms periods**

Covariate	Transition	2005–2016	*IR* = 0	*IR* = 1	Pairwise comparison (Post minus Pre-reforms)
a) Estimated probabilities					
	Remain as a zombie	0.7276***	0.7502***	0.6694***	−0.0808***
	Recovery	0.1268***	0.1064***	0.1676***	0.0612***
	Exit	0.1456***	0.1434***	0.1630***	0.0196***
b) Average marginal effects (AMEs):					
TFP	Remain as a zombie	0.0187***	0.0323***	−0.0051*	−0.0374***
	Recovery	0.0506***	0.0420***	0.0691***	0.0271***
	Exit	−0.0693***	−0.0743***	−0.0641***	0.0103***
Capital	Remain as a zombie	0.0135***	0.0131***	0.0108***	−0.0022
	Recovery	0.0024***	0.0054***	−0.0023*	−0.0077***
	Exit	−0.0159***	−0.0185***	−0.0086***	0.0099***
Labour	Remain as a zombie	0.0096***	0.0080***	0.0055**	−0.0025
	Recovery	0.0067***	0.0043***	0.0189***	0.0146***
	Exit	−0.0163***	−0.0123***	−0.0244***	−0.0121***
Leverage	Remain as a zombie	−0.0148***	−0.0303***	0.0133***	0.0436***
	Recovery	−0.0402***	−0.0296***	−0.0671***	−0.0375***
	Exit	0.0550***	0.0599***	0.0538***	−0.0061**

Notes: Multinomial logit model (Observations: 198,104; Wald chi2: 20130.74; Pseudo R^2: 0.0841; Log pseudolikelihood: −140407.6). *TFP*, *Capital*, *Labour* and *Leverage* are in logs. *IR* is a dummy that takes the value of one for years greater than 2012 (i.e., the post-reforms period). The pairwise comparison between marginal effects expresses the interaction effect, that is, the difference in effects between the "zombies after the reforms" and the "zombies before the reforms". The estimates of control variables including log of cash-flow, log of age, log of zombie duration, business cycle measure, and industry and location dummies are not reported in the table. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

The greater the financial distress of the zombies, the lower (higher) their likelihood of transitioning into recovery (exit). The pairwise comparison of AMEs between the periods is negative in both cases (-3.8 and −0.6 p.p., respectively). Apparently, from this perspective, the reforms were not efficient. These results suggest that instead of reducing the forbearance of creditors, the reforms have increased it; and that the attempts to refinance the debt were unsuccessful, increasing the probability of zombie survival, as shown by the positive sign and the statistical significance of the interaction effect on the likelihood of "remaining as a zombie".

Looking at the effects of firm size on the transitions of zombies, the larger the firm (proxied by capital and labour), the higher (lower) its probability of recovery (exit). However, since size had a greater effect on the likelihood of exit than on the likelihood of recovery, there is a positive relationship between size and the non-transition probability. This is consistent with the hypothesis that the larger the company, the more likely it is to remain in the zombie status. This result confirms our CPH estimates. The impact of the reforms on the likelihood of recovery and exit goes in opposite directions, depending on whether the size is proxied by capital or employment. The positive (negative) relationship between capital and recovery (exit) reduced by 0.8 (1.0) p.p. in the post-reforms period, while the positive (negative) relationship between employment and recovery (exit) increased by 1.5 (1.2) p.p.

We have also followed Williams (2012) and computed the adjusted conditional probabilities at representative values of the (log) capital and labour, in the pre and post-reforms periods. Table 8.3 reports the revised predictions, for each transition, of two otherwise identical zombies that differ only in size. The relevant values are given by the sample average value of each covariate, by size category (SMEs and large zombies). According to the table's penultimate column, which gives the difference in expected probabilities between treatment and control groups, the recovery likelihood of an average small-in-capital zombie rose 6.2 p.p. in the post-reform's interval. In comparison, in a typical large-in-capital zombie the increase was only 3.1 p.p. It seems that the positive relationship between capital and recovery is weakened not because large-in-capital zombies reduce their chances of reorganisation, but because the increase in the probability of recovery is higher in small-in-capital zombies. Therefore, the estimates suggest that, by encouraging reorganisation agreements, the impact of the reforms was more significant in small-in-capital businesses. This was probably due to the fact that these types of firms have a lower number of creditor classes, which simplifies the coordination of the agreement. Additionally, since the larger the capital, the more outstanding the debt (in absolute terms), the resolution of financial distress is relatively delayed. Nevertheless, the effect of the institutional changes was positive in financially distressed large firms.

In the case of exit, although the liquidation probability increased in both types of zombies, the rise was 2.8 p.p. higher in those large-in-capital, as shown in the pairwise comparison in the last column of the Table. The exit likelihood of a typical small-zombie increased from 14.0% to 16.2%, compared to an increase of 8.0% to 13.1%. for the average large-zombie. Thus, even though the negative relationship between capital-size and exit likelihood was maintained after the reforms, the exit-risk gap between large and small financially distressed firms has reduced. This finding suggests that SMEs are relatively less prone to liquidation. However, given that the increase in the exit probability is more than twice as large in the representative large company, it seems that capital intensity also plays an important role in the changes in liquidation probability.

Table 8.3 Estimated probabilities using average size (capital and labour)

Variable	Transition	Size	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Difference in expected probabilities	Pairwise comparison (Large vs SME)
Capital	Remain as a zombie	SME	0.7297***	0.7538***	0.6697***	−0.0841***	0.0029
		Large	0.7702***	0.7922***	0.7110***	−0.0811***	
	Recovery	SME	0.1255***	0.1058***	0.1680***	0.0622***	−0.0311***
		Large	0.1364***	0.1274***	0.1585***	0.0311***	
	Exit	SME	0.1449***	0.1404***	0.1623***	0.0219***	0.0282***
		Large	0.0934***	0.0804***	0.1305***	0.0501***	
Labour	Remain as a zombie	SME	0.7296***	0.7519***	0.6722***	−0.0797***	−0.0192**
		Large	0.7412***	0.7716***	0.6727***	−0.0989***	
	Recovery	SME	0.1275***	0.1064***	0.1671***	0.0607***	0.0472***
		Large	0.1556***	0.1192***	0.2271***	0.1079***	
	Exit	SME	0.1430***	0.1417***	0.1607***	0.0190***	−0.0280***
		Large	0.1032***	0.1092***	0.1002***	−0.0090	

Notes: Multinomial logit model. *IR* is a dummy that takes the value of one for years greater than 2012 (i.e., the post-reforms period). Columns 1, 2 and 3 report the estimated probabilities for the "average" firm in each representative value, where "average" means that the estimate is conditional on the actual observed values for the other explanatory variables including the other size value. The difference in expected probabilities expresses the interaction effect in each representative size-value. The estimates of TFP, leverage and the control variables including the log of cash-flow, log of age, log of zombie duration, business cycle measure, and industry and location dummies are not reported in the table. Standard errors (not reported) for statistical significance tests were obtained using the delta-method. ***, ** and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Regarding employment-size, the upsurge in the recovery probability of an average large-in-employment zombie is 4.7 p.p. higher than that of its small counterpart (pairwise comparison column). Thus, as a result of commanding more resources and having higher managerial capabilities, large companies seem to achieve a successful restructuring in a shorter time, taking advantage of the new institutional framework. In relation to the exit transition, only the change in expected probabilities in the representative SME is statistically significant and, in effect, its exit likelihood increases 1.9 p.p. in the post-reforms period. Therefore, we have the result that the negative relationship between size-in-employment and liquidation probability increases after the reforms, which suggests that the "too big to fail" effect is likely to have played a crucial role in insolvency events.

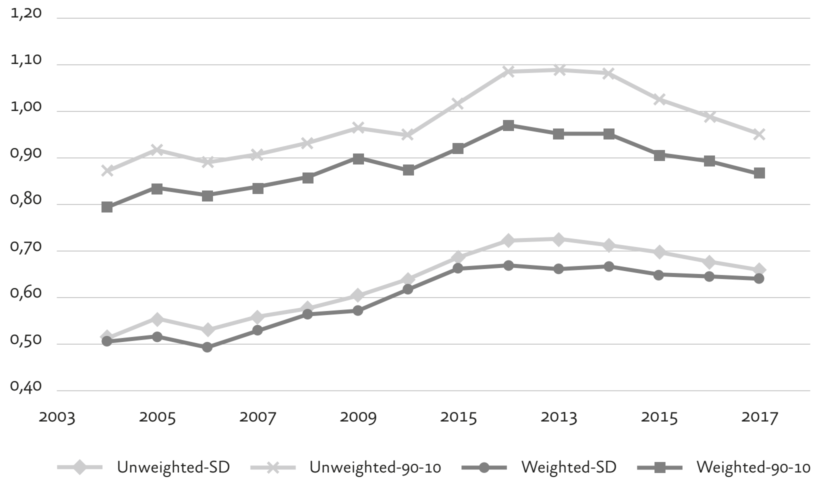
Overall, the results suggest that the reforms effectively reduced the barriers that hinder the transition of zombies to both recovery and exit. Since not all zombies are unviable firms, the implemented reform was a more appropriate and efficient route, as it encouraged reorganisation to prevail over liquidation in financially distressed firms. At the same time, both large and small companies increased their reorganisation likelihood, an indication that the reforms not only mitigated delays in resolving insolvency conflicts, which are characteristic of large companies with many creditors, but also somehow complemented the lower bargaining power of small businesses. Unfortunately, the prevalence of zombies was also reduced by a misleading selection at the exit margin, since more productive firms are not free from the risk of liquidation.

8.5. The effect of reforms on productivity dispersion

Under fewer reallocation barriers, the productivity gap between zombies and non-zombies is smaller, which reduces the within-industry productivity dispersion (Caballero et al., 2008). Figure 8.2 shows the evolution of the technological dispersion within industries, measured by the productivity differential between the 90 and 10 percentiles and by the standard deviation of the TFP distribution (unweighted and weighted by output-industry-shares).

As we can see, there is a positive trend in productivity dispersion up to the 2012 reforms. After 2012, there has been a slight reduction in TFP dispersion, which is consistent with the prediction of Caballero et al. (2008). This result is also consistent with the responsiveness hypothesis of Decker et al. (2018), who pointed out that when adjustment costs (or frictions, in a broader sense) are lower, the effect of idiosyncratic productivity on business growth is greater and the productivity dispersion is lower.

Figure 8.2 Within-industry TFP dispersion



Notes: The graph shows the standard deviation (SD) and the 90 to 10 percentiles differential of the within-industry log TFP (as a deviation from the industry mean). Unweighted and weighted measures (output-industry-share as weights).

Chapter 9
Business dynamics and industry productivity growth

Given the sizable reallocation of resources across firms observed in the previous chapters, we finally analyse its contribution to industry productivity growth. As mentioned earlier, resource reallocation per se does not generate aggregate productivity growth, but the process of productivity growth requires ongoing productivity-enhancing reallocation. To assess the specific contribution of each business dynamics effect, we decompose the industry productivity growth into three components: within, covariance, and net-entry. Since the process of creative destruction may take time, the decomposition was conducted using four-year periods.

9.1. Decomposition method of aggregate productivity growth

We define the aggregate productivity level in year t, P_t, as a share-weighted average of firm productivity p_{it}, that is,

$$P_t = \sum_i \theta_{it}\, p_{it}, \qquad (9.1)$$

where θ_{it} is the share weight of the ith firm in year t and pit is the corresponding productivity level. There are different possibilities for the choice of a productivity measure and associated share weight. As in Foster et al. (2001) and Carreira and Teixeira (2008), we selected the TFP and labour productivity in logarithms as our productivity measures, and the underlying share weights as the output and employment shares, respectively.

Clearly, industry productivity growth can occur either through changes in the productivity level across firms or through changes in their market shares, which reflects the entry, exit and expansion/contraction of continuing firms. In order to understand the role of resource allocation in productivity change, we decompose the aggregate productivity growth using an extended version of the Olley and Pakes (1996) decomposition method proposed by Melitz and Polanec (2015):[23]

$$\Delta P_t = \underbrace{\Delta \bar{P}_{Ct}}_{\text{Within effect}} + \underbrace{(\Delta\, cov_{Ct}(\theta_{it}, p_{it})}_{\text{Between effect}} + \underbrace{\theta_{Et}(P_{Et} - P_{Ct})}_{\text{Entry effect}} + \underbrace{\theta_{X(t-\tau)}(P_{C(t-\tau)} - P_{X(t-\tau)})}_{\text{Exit effect}}, \qquad (9.2)$$

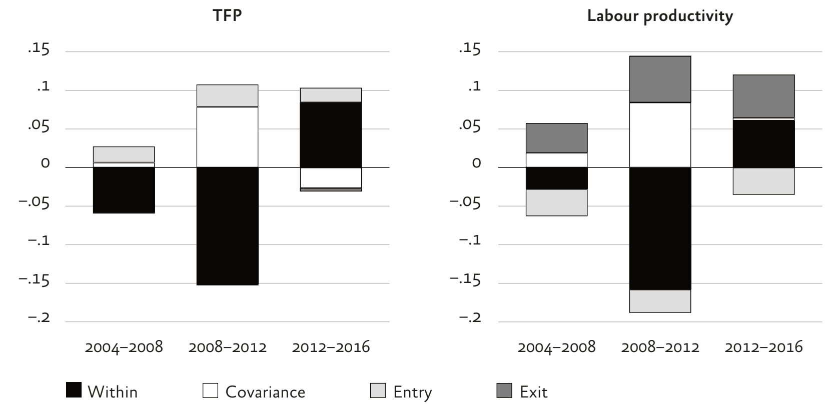
where Δ denotes changes between $t\!-\!\tau$ and t (since the productivity change is measured in differences and the productivity measure is in logarithm, ΔP_t represents a percentage change); C, E, and X denote the group of continuing, entering, and exiting firms (the group of continuing firms comprises all existing firms in the beginning of the period that remain active throughout the period); and θ_{gt} is the share of group g, and P_{gt} and $\bar{P}_{gt}$ are the corresponding weighted and unweighted average productivity ($g = C, E, X$). The first term on the right-hand side of Equation (9.2), called the "within" term, captures the contribution of within-firm productivity changes of continuing firms. The second term, the "covariance" term, reflects the inter-firm resource reallocation towards more productive continuing firms. In this case, any gains in aggregate productivity will come from increasing (decreasing) shares of continuing firms with a higher (lower) productivity. The last two terms capture the contribution of entering and exiting firms, respectively. The entry (exit) contribution is positive if the productivity level of entering (exiting) firms is higher (smaller) than the productivity level of continuing firms in the corresponding year.

Under the cleansing hypothesis, we expect that less productive firms either contract further or exit in response to a strong negative shock. That is, we should expect increases in the covariance term, as well as in the entry and exit terms. By contrast, under the scarring effect, we should expect the downsizing and the exiting of high-productivity financially constrained firms *and* the growth of low-productivity financially unconstrained firms. We should also expect a decrease in the within-firm term since, in times of credit market retractions, incumbent firms tend to invest in less productive projects.

9.2. Quantifying the effect of business dynamics on industry productivity growth

We analyse the contribution of reallocation to industry productivity growth over three subperiods of equal length: 2004–2008 (stagnation), 2008–2012 (recession) and 2012–2016 (recovery).[24] The results of the dynamic Olley–Pakes decomposition exercise, both for the economy as a whole and by sector, are given in Figure 9.1 and Table 9.1, respectively. The weakness of productivity growth during the recession seems to be primarily due to a sharp fall in the within term, which was not entirely offset by the productivity-enhancing effects of reallocation. Specifically, the within component subtracted 15.1 (15.8) p.p. from TFP (labour productivity) growth in 2008–2012, while the reallocation between continuing firms added 7.9 (8.4) p.p., and the net-entry term another 2.7 (3.0) p.p. As a result, the 2012 TFP (labour productivity) was 4.5 (4.4)% below the 2008 level.

Figure 9.1 Productivity growth decomposition



Notes: Decomposition of four-year change in TFP (labour productivity) with output (employment) shares as weights using the dynamic Olley–Pakes method at the two-digit industry level. Aggregation weighted by firm's output (TFP) and employment (labour productivity).

Figure 9.1 also shows that the contribution of reallocation to productivity among continuing firms was more intense in 2008–2012 than in 2004–2008. In 2012–2016, the contribution was negative. This sharp increase in the covariance term during the crisis, from 0.6 (1.9) p.p. to 7.9 (8.4) p.p., suggests that continuing firms with a large decline in TFP (labour productivity) also have a higher contraction in output (employment), a result that is favourable to the cleansing hypothesis. However, as we have seen, the (large) negative within term also indicates that the crisis generated sizeable counterproductive destruction, possibly driven by the adverse credit supply shock.

Table 9.1 Productivity growth decomposition by sector

	TFP				Labour productivity			
	Growth	Within	Covariance	Net entry	Growth	Within	Covariance	Net entry
				2004-2008				
Manufacturing	0.024	-0.010	0.015	0.020	0.017	-0.035	0.035	0.017
Construction	-0.145	-0.127	-0.052	0.034	-0.022	-0.037	0.016	-0.001
Trade	-0.009	-0.063	0.035	0.018	0.005	-0.041	0.038	0.008
Accommodation	-0.031	-0.059	0.026	0.001	-0.021	-0.033	0.021	-0.009
Real estate	-0.141	-0.126	-0.038	0.023	-0.020	-0.005	0.004	-0.019
Business services	-0.040	-0.027	-0.039	0.026	-0.023	0.010	-0.026	-0.007
				2008-2012				
Manufacturing	0.021	-0.097	0.098	0.021	-0.005	-0.144	0.094	0.046
Construction	-0.086	-0.298	0.163	0.048	-0.073	-0.230	0.116	0.041
Trade	-0.110	-0.201	0.057	0.034	-0.085	-0.162	0.043	0.035
Accommodation	-0.100	-0.210	0.099	0.011	-0.119	-0.225	0.115	-0.008
Real estate	-0.097	-0.418	0.300	0.021	-0.094	-0.102	0.004	0.003
Business services	-0.038	-0.109	0.037	0.034	0.019	-0.118	0.114	0.022
				2012-2016				
Manufacturing	0.029	0.046	-0.023	0.006	0.090	0.044	0.025	0.021
Construction	0.006	0.062	-0.067	0.011	0.052	0.059	-0.047	0.039
Trade	0.154	0.137	-0.015	0.032	0.148	0.087	0.040	0.021
Accommodation	0.085	0.090	-0.014	0.008	0.098	0.075	0.022	0.001
Real estate	-0.003	0.098	-0.108	0.007	0.049	0.051	0.002	-0.003
Business services	0.032	0.045	-0.038	0.025	0.016	0.044	-0.050	0.021

Note: See Figure 9.1 notes.

There was also an increase in the net-entry contribution during the Great Recession. For instance, net-entry added 2.7 (3.0) p.p. to TFP (labour productivity) growth, compared to 2.0 (0.3) p.p. and 1.5 (2.0) p.p., before and after the crisis, respectively, which suggests an increase in the efficiency of resource allocation during the Great Recession.

In the recovery period, the productivity growth is fully explained by the within component, while the between component is negative.

The main findings remain valid across sectors, albeit at different magnitudes (Table 9.1). Overall, the data does seem to support the hypothesis that in times of credit market retractions incumbent firms tend to invest in less productive projects. The observed weakness of productivity growth during the Great Recession is associated with an across-the-board decline in productivity within firms. There was also an increase in the resource reallocation components during the Great Recession, which is favourable to the cleansing hypothesis. However, this contribution is not sufficiently strong to offset the sharp decline in the within component.

Chapter 10
Conclusion

Two years ago, when we began this study, we were all far from imagining that a new crisis was on the horizon. In this study, we take advantage of a natural experiment, the Great Recession (2008–2013), to highlight the role of stringent credit market frictions on economic performance. We hope our findings will serve as a useful guide to policymaking in the new COVID-19-dominated context, as they show that deep recessions are primarily periods of counterproductive destruction rather than productive cleansing.

We use an extended longitudinal panel of manufacturing and services firms over 2004–2017. In this interval, we document large and persistent differences in firm-level productivity, even in narrowly defined industries. The observed dispersion in productivity across Portuguese firms is also increasing over time. Moreover, during the Great Recession, there were both a shift to the left of the productivity distribution (i.e., towards lower levels of productivity) and a contraction of the right tail, populated by relatively fewer high-productivity firms.

The persistent heterogeneity in firm-level productivity suggests a high resource misallocation. Firstly, we observe a slowdown in job creation and an increase in job destruction during the recession, but no evidence of a countercyclical job reallocation, which contradicts the expected cleansing effect of recessions. Secondly, at least half of the jobs destroyed were in firms above the median productivity level, while a number of low-productivity firms have created jobs. Interestingly, the share of job creation by low-productivity firms was higher at the peak of the crisis. Finally, the share of jobs created by firms below the industry-median leverage and the share of jobs destroyed by firms at the top quantile of the leverage increased during the period under analysis.

There were fewer, although more productive, entrants during the recession, and the survival productivity threshold increased, as predicted by the cleansing effect theory, resulting in a higher exit rate. However, the leverage ratio of about two-thirds of the entering firms was higher than the industry median. Perhaps because mortality is higher among newly born firms, and their likelihood of exit is higher in the case of high leverage. A similar share was observed for exiting firms.

The econometric analysis confirms that low-productivity firms have a higher probability of exiting and grow slower than their high-productivity counterparts. Credit market conditions, however, play a crucial role. Throughout the crisis, high-productivity firms exit or grow at a slow pace because they are financially constrained, which is compatible with the scarring hypothesis. Moreover, the risk of exiting is higher for firms with weaker pre-crisis balance sheets and for firms operating in industries with higher financial dependency.

Zombie firms are across-the-board and are significantly less productive than non-zombies. Furthermore, resources sunk by zombies have risen during the Great Recession. If artificially sustained, zombies are expected to prevent aggregate productivity growth. In our analysis, the 2012 reform of the insolvency regime proved to be efficient in reducing the reallocation barriers, considering that the entrenchment time of zombie firms was shortened due to an increased likelihood of recovery and exit. Accordingly, the adverse impact of zombies on productivity-enhancing resource reallocation decreased in the post-reforms period.

Finally, our findings point to a decline in productivity growth within firms as the primary cause of the low industry productivity growth during the Great Recession. This result supports the hypothesis that in times of strong credit market restrictions, incumbent firms tend to avoid high-productivity/high-risk projects. Interestingly, although there was an increase in the contribution of business dynamics during the Great Recession, it was not sufficiently strong to offset the sharp decline in the within effect, as predicted by the cleansing hypothesis.

Overall, if the cleansing hypothesis prevails in slump periods, a V-shaped upturn is more likely to occur. However, our results suggest that financial constraints, distorted incentives, negative externalities and imperfect foresight are intensified in credit markets in a scenario of adverse and extended collapse. Altogether, these factors can lead to a resource misallocation that severely undermines the recovery period. Therefore, credit market stringency in conjunction with an unfavourable economic cycle is not unlikely to generate a long-lasting destructive process.

These findings have a crucial implication for the design of public policies aimed at reducing the costs of recessions and boosting recovery. This is, of course, a relevant matter in the current COVID-19 context. Given the magnitude of the negative shock, a further deterioration in firm balance sheets will most certainly trigger bankruptcy and an uptick in the exit risk of a significant share of viable firms. Therefore, counter-cyclical policies intended to relieve companies' liquidity problems are of potentially great importance as they mitigate the long-run consequences of great recessions. However, an approach that does not discourage creditors from refinancing non-viable firms is not likely to improve efficiency.

Insolvency regimes designed to facilitate proper corporate restructuring seem to be an effective vehicle to ensure an efficient deleveraging. Our results suggest that a coordinated and holistic restructuring strategy (technology, operations and debt-related) increases the likelihood of recovery for weak companies. Our analysis also shows that an adequate balance between debtors and creditors' rights, in the bankruptcy legislation, can increase the probability of viable but financially distressed firms to transition into recovery. It is worth noting that the standard legal insolvency procedures were designed to deal with idiosyncratic events and, therefore, when a large-scale shock hits the entire economy, conflict resolution is unlikely to consider the externalities that a series of micro-events may cause at the aggregate level. Therefore, the implementation of a coordinated macro-level agenda – that both encourages capital restructurings (via capital injections into preference shares or unsecured debt, debt-equity swaps, inter al.) *and* deters moral hazard and zombie lending – is likely the best route. However, we must point out that restructuring and insolvency involve significant welfare costs (e.g., unemployment), which should also be a matter of concern for Governments.

Our findings also set new challenges to the research agenda: Given that highly indebted yet productive firms were forced to exit, while zombies benefited from evergreen lending, then, what is the size of the welfare loss associated with a process that retains the least productive firms? In the same vein: In a credit-constrained market where ideas are not contractible, and loans are issued on a collateralised basis, does the threat of systemic bankruptcy play any role in creditors' behaviour and in the way destruction takes place? These are just a few examples that illustrate that understanding exit selection in deep recessions is very much an unfinished business.

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Notes

1. Bartelsman and Doms (2000) and Syverson (2011) provide interesting surveys.

2. Caves (1998) and Bartelsman et al. (2005) provide interesting surveys in this respect.

3. The analysis comprises the following countries: Belgium, Finland, France, Italy, Korea, Slovenia, Spain, Sweden and the United Kingdom. In addition, for the 2013 cross-sectional study, Austria, Germany, Luxembourg and Portugal were added.

4. Austria, Denmark, Estonia, France, Germany, Greece, Latvia, Slovenia, Spain, Portugal, United Kingdom.

5. We also computed TFP using both the Olley and Pakes (1996) and the Blundell and Bond (2000) two-step system GMM estimates, as a robustness check, with no major changes in the results. These results are available from the authors on request.

6. In order to understand how the shape of a Lévy alpha-stable distribution changes with different values for the four parameters, see Yang et al. (2019, p. 10).

7. We use the quantile-based estimator proposed by McCulloch (1986).

8. The job creation and destruction rates by entering and exiting firms are relatively lower than those reported by Carneiro et al. (2014). This is mainly due to differences in the unit of observation. Our analysis is conducted at the firm level, whereas the analysis of Carneiro et al. (2014) is conducted at the establishment level.

9. There is no clear methodology to evaluate whether firms are financially constrained (Carreira and Silva, 2010; Coad, 2010). The most practical and simple way to measure firms' financial constraints is the use of proxies. Cash-flow and leverage are the most used proxies in the empirical literature (Carreira et al., 2020a).

10. The ICFS model was estimated at the industry level using the first difference GMM estimator.

11. Note that $1 - \exp(-0.206) = 1 - 0.814 = 0.186$ and $1 - \exp(-0.182) = 1 - 0.834 = 0.166$.

12. In the former case, we performed the Breusch and Pagan Lagrangian multiplier test and the Hausman test and, in the latter, a modified Wald test for groupwise heteroscedasticity.

13. The investment projects of young firms need time to deliver returns. We use the 5-year threshold because it is the age limit defined by the OECD for young high-growth firms (Ahmad, 2006; Koski and Pajarinen, 2013). Most studies point out that firms achieve their mature state somewhere between their sixth and tenth year of existence (Carreira and Teixeira, 2011). We also checked the 10-year limit used by McGowan et al. (2018), as a robustness test, with no major changes in the results.

14. We exclude from our sample micro-enterprises that persistently have less than three employees, as they are generally self-employment enterprises, for whom the generation of profits, growth, and innovation are not primary motivations. Their main goal is to generate enough activity and revenue for themselves (i.e., for the family).

15. McGowan et al. (2018) also tested different variations of their criteria with no visible sensitivity, while Schivardi et al. (2017) and Storz et al.'s (2017) replication of the definition of McGowan et al. produced only a very limited impact on the results.

16. The results are robust to alternative definitions of zombie firms. Actually, our shares of zombie firms are on average 1.7 p.p. higher than those computed with the definition of interest coverage ratio of McGowan et al. (2017a) (in 2010–2016), and 1.3 p.p. lower than those estimated with the original definition of Schivardi et al. (2017). Clearly, the three alternatives show a similar pattern over time.

17. The increase of the VAT rate for restaurants from 13% to 23% in 2012 is certainly an explanation for the large increase in the number of zombie firms.

18. Note that $e^{-0.054} - 1 = -0.053$ and $e^{-0.108} - 1 = -0.102$.

19. The results are robust to the definitions of zombie firms by Shen and Chen (2017), Schivardi et al. (2017) and McGowan et al. (2018). We also checked their robustness using an ordered logit model. In both cases, there are no significant changes in the sign and in the statistical significance of the average marginal effects of key explanatory variables.

20. Directorate-General for Justice Policy (Quarterly Statistical Highlight, Bulletin No. 60) and IAPMEI (Informative Summary, December 2018).

21. As pointed out by Buis (2010), if we find that the baseline odds do not have a statistically significant change over the interval, the sign of the coefficients associated with the interactions should give us the same sign of the pairwise comparison between the (post and pre-reforms) marginal effects of the corresponding regressor. However, the fact that the marginal effects add up to zero simplifies the interpretation of the changes in transition probabilities before and after the reforms.

22. The finding is confirmed using labour productivity.

23. Alternative decomposition methods and how they affect the decomposition of aggregate productivity can be found in Foster et al. (2001), Baldwin and Gu (2006) and Melitz and Polanec (2015).

24. The second sub-period should have been extended until 2013. However, due to the learning effect, the results of the different subperiods are only comparable if they have equal length.

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