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UNIVERSIDADE D
COIMBRA

José Ernesto Nieto Carrillo

The (in)stability of Creative Destruction

Industrial dynamics and Productivity Growth in Portugal over the last four decades

Tese no âmbito do Doutoramento em Economia orientada pelo Professor Doutor Carlos Manuel Gonçalves Carreira e pelo Professor Doutor Paulino Maria Freitas Teixeira e apresentada à Faculdade de Economia da Universidade de Coimbra.

Dezembro de 2022

1 2 9 0 FACULDADE DE ECONOMIA UNIVERSIDADE D COIMBRA

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Tese no âmbito do Doutoramento em Economia, apresentada à Faculdade de Economia da Universidade de Coimbra para obtenção do grau de Doutor

Orientadores: Professor Doutor Carlos Manuel Gonçalves Carreira e Professor Doutor Paulino Maria Freitas Teixeira

Dezembro de 2022

For Vicky and Pepe, for who I am,
and Tiago, for who I want to be.

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It could be argued that completing a doctoral thesis is solely the result of a sustained research effort over the time it lasted. Nevertheless, the objectives set and how said work is carried out fundamentally reflect a mental and behavioural structure acquired throughout life. Accordingly, this thesis has benefited from the people who have accompanied and supported this process in the last five years and those who have contributed to my overall personal and academic formation.

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Resumo

Schumpeter defendeu que a destruição criativa é o impulso fundamental responsável por manter a máquina capitalista em movimento, através de inovações incessantes que tornam obsoletas velhas ideias e tecnologias. Esta tese investiga a estabilidade a longo prazo deste processo dinâmico, nomeadamente através da análise da dinâmica industrial portuguesa ao longo das últimas quatro décadas. Em particular, explora, por um lado, a evolução do empreendedorismo, da reafectação de recursos, do regime competitivo e do crescimento da produtividade no setor KIA (atividades intensivas em conhecimento) versus o setor não-KIA e, por outro, a prevalência da seleção de mercado schumpeteriana versus a não-schumpeteriana. Como hipótese central propõe-se que a desaceleração da produtividade é uma função crescente da seleção não-schumpeteriana.

Após o surgimento da revolução das TIC na década de 1980, os países industrializados beneficiaram de um crescimento económico relativamente estável durante cerca de vinte anos. No entanto, ao longo das duas décadas seguintes, o crescimento e o progresso técnico diminuíram na maioria dos países desenvolvidos, com um número crescente de estudos a analisar a respetiva causa. Todavia, e com exceção dos estudos abrangendo a economia norte-americana, a maioria dos trabalhos encontra-se baseada em dados microeconómicos observados centrados nos últimos vinte anos. Dada esta limitação, esta tese procura focar-se num período bem mais longo, compreendido entre 1986 e 2018 e utilizando uma classificação setorial plenamente consistente no tempo e transversal à população de empresas portuguesas do setor transformador e dos serviços.

A análise baseada no filtro de Hodrick-Prescott (HP) indica uma marcada mudança estrutural na dinâmica industrial a partir do início do novo século. Durante o período pré-2000, a reafectação de empregos aumentou, enquanto as empresas recém-nascidas e empresas jovens desempenharam um papel crítico na criação líquida de empregos. Ao mesmo tempo, as indústrias exibiam em geral uma maior instabilidade, uma concentração decrescente, um hiato de inovação mais significativo entre líderes e seguidores e uma menor probabilidade de preservar a liderança industrial. Foram ainda observados indicadores de dinâmica industrial mais intensa no setor KIA, confirmando-se assim a teoria schumpeteriana de ciclos de inovação de longo prazo.

Esta tendência, porém, não se manteve no período pós-2000, mesmo no caso das indústrias KIA. Nas últimas duas décadas, as empresas emergentes viram a sua participação diminuir, apesar de um melhor nível de desempenho de empresas jovens de alto crescimento. O regime competitivo também ficou mais fraco e as empresas dominantes aumentaram sua quota de mercado, bem como a probabilidade de manter a liderança não obstante a diminuição do esforço de novação. As regressões ao nível setorial sugerem ainda que o aumento da concentração não só debilitou os incentivos para as empresas líderes inovarem como também facilitou a preservação de posições dominantes. Por seu turno, as regressões em painel, de efeitos fixos ao nível da empresa, indicam que quanto maior a concentração industrial, menor o efeito do crescimento da produtividade na expansão da quota de mercado. Por fim, a nossa análise indica um aumento da prevalência de empresas zombie, ou seja, de empresas não lucrativas e altamente endividadas. Essa maior incidência de zombies teve como efeito a redução da produtividade agregada, devido a uma reafectação de recursos económicos ineficiente e a externalidades negativas sobre projetos saudáveis. Os modelos de *treatment effects*, multinominais e de efeitos fixos mostram que as reformas de insolvência de 2012, favoráveis em geral aos devedores, reduziram quer o grau de sobrevivência das zombies quer a influência negativa na reafectação de recursos.

Os nossos resultados sugerem assim que a destruição criativa se pode tornar instável no longo prazo, confirmando-se desta forma uma hipótese central, de que a desaceleração da produtividade é uma função crescente da seleção de mercado não-schumpeteriana, isto é, da concentração e saída não-schumpeterianas.

PALAVRAS-CHAVE: Dinâmica industrial; Concorrência; Crescimento da produtividade; Empreendedorismo; Empresas zombie.

Abstract

Schumpeter argued that creative destruction is the fundamental impulse responsible for keeping the capitalist machine in motion through incessant innovations that make old ideas and technologies obsolete. The thesis investigates the long-term stability of this dynamic process by analysing the Portuguese industrial dynamics over the past four decades. In particular, it explores the evolution of entrepreneurship, reallocation, competitive regime and productivity growth in the KIA (i.e., knowledge-intensive activities) versus the Non-KIA sector and the prevalence of Schumpeterian versus non-Schumpeterian market selection. The primary hypothesis of this thesis is that productivity slowdown is an increasing function of non-Schumpeterian selection.

After the emergence of the ICT revolution in the 1980s, industrialised countries benefited from relatively stable growth for about twenty years. Nonetheless, growth and technical progress have slowed down in most developed countries during the new century, with an increasing body of research analysing the underlying causes. However, except for the US studies, most micro-based research has only been grounded on new-century evidence. Given this limitation, this thesis focuses on a longer period, assembling an extensive longitudinal database with a time-consistent industry classification that covers the population of manufacturing and service sector firms from 1986 to 2018.

The Hodrick-Prescott (HP) trends indicate a structural change in industrial dynamics since 2000. Before 2000, job reallocation increased while newly-born and young firms played a leading role in net job creation. Meanwhile, the typical industry also exhibited higher instability, decreasing concentration, a more significant innovation gap between leaders and followers, and a lower probability of preserving industrial leadership. Moreover, higher industrial dynamics indicators were observed in the KIA sector, thus supporting the Schumpeterian theory of long-term innovation cycles.

This process came to a halt in the new century, even in the KIA industries. In the last two decades, nascent companies have seen a declining incidence, notwithstanding the better performance of young, high-growth firms. In addition, the competitive regime has weakened, and dominant firms have increased their market share and the likelihood of retaining leadership despite diminishing innovative efforts. Industry-level regressions further suggest that increased concentration has weakened incentives for leading firms to innovate while facilitating the preservation of dominant positions. At the same time, firm-level fixed effects panel regressions indicate that the higher the industrial concentration, the smaller the effect of productivity growth on market share expansion. Finally, we found an increased prevalence of unprofitable/highly indebted firms (i.e., zombies). This higher incidence of zombies has also undermined aggregate productivity due to inefficient reallocation and negative externalities on healthy projects. Nevertheless, the treatment effects, multinomial logistic, and fixed-effects panel estimators show that the 2012 debtor-friendly insolvency reforms did reduce zombie survival as well as the negative influence on resource reallocation.

Altogether, these findings suggest that creative destruction becomes unstable in the long term, thus confirming our main hypothesis that the productivity slowdown is an increasing function of non-Schumpeterian market selection, namely of the non-Schumpeterian concentration and exit selection.

KEYWORDS: Industrial dynamics; Competition; Productivity growth; Entrepreneurship; Zombie firms.

List of Acronyms and Abbreviations

AME	Average marginal effects
AMECO	Annual macro-economic database of the European Commission
ATEs	Average treatment effects
ATETs	Average treatment effects on the treated
CAE	Portuguese Classification of Economic Activities
CIRE	Insolvency and Company Recovery Code
EBA	European Banking Authority
EBITDA	Earnings Before Interests, Taxes, Depreciations and Amortizations
ECB	European Central Bank
EU	European Union
EUROSTAT	Statistical Office of the European Union
FUE	Ficheiro das Unidades Estatísticas
GDP	Gross Domestic Product
HGF	High-growth firms
HHI	Hirschman-Herfindahl Index
HP	Hodrick-Prescott
IAPMEI	Portuguese Agency for Competition and Innovation
ICT	Information and Communication Technologies
ILO	International Labour Organisation
INE	National Statistical Office
IPE	Employment Protection Index
IPRs	Intellectual Property Rights
ISCED	International Standard Classification of Education
KIA	Knowledge Intensive Activities
M&A	Mergers and Acquisitions

NACE	Statistical classification of economic activities in the European Community
NNM	Nearest Neighbour Matching
NPLs	Non-productive loans
NUTS	Nomenclature of Territorial Units for Statistical Purposes
N/A	Not applicable
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PER	Special Revitalisation Process
p.p.	Percentage points
QP	Quadros de Pessoal
Rev.	Revision
RLP	Revenue Labour Productivity
R&D	Research and Development
SCIE	Sistema de Contas Integradas das Empresas
SIREVE	Extrajudicial Business Recovery System
SME	Small and Medium-sized Enterprises
TFP	Total factor productivity
UK	United Kingdom
US	United States

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1 Introduction

1.1 The theoretical and institutional context

Technical progress has historically been one of the topics that have most aroused the interest of economists. All theoretical approaches recognise its importance as a critical variable in encouraging long-term growth. After all, the ability to produce more efficiently has been considered synonymous with development and a determining factor in the "wealth of nations" since the foundation of economic theory. However, there has been anything but a consensus on the market and institutional conditions that must prevail to promote it.

After the stagflation crisis that gripped most advanced economies during the 1970s, the resulting decline of Keynesian postulates, and the Soviet bloc's collapse, most governments reoriented their policies towards market liberalisation as a mechanism for economic growth and income distribution (Piketty, 2020; Rodrik, 2006). At the same time, the global economy saw the rise of the Information and Communication Technologies (ICT) revolution, a new technological paradigm that triggered the emergence of new markets and the reconfiguration of productive trajectories in traditional industries. In this new institutional and technological context, the economy of the industrialised nations enjoyed relatively sustained and stable growth for around two decades.

Nonetheless, growth and technical progress have weakened in most developed countries during the new century and even before the pandemic crisis. Along the same lines, several studies show a declining business dynamism (Calvino et al., 2020; Decker et al., 2016), greater market concentration (Autor et al., 2017; Bajgar et al., 2019), and a significant fall in aggregate wage shares (Karabarbounis & Neiman, 2014).

The phenomenon of productive stagnation has gone hand in hand with a loss of theoretical predominance of the neoclassical paradigms of perfect competition and exogenous technical change. The emergence of extensive microeconomic, longitudinal and intersectoral datasets has allowed more robust empirical studies that have cast doubt upon the assumptions on which these approaches rely and, therefore, their ability to explain market behaviour. Although the resulting inference from these studies might be that markets are inefficient and growth and fair distribution require public intervention, much of the mainstream literature has migrated towards the Schumpeterian standpoint regarding competition and technical progress.

Given the sunk-cost nature of innovation and entrepreneurship, knowledge non-rivalry, and structural uncertainty, no rational firm would undertake efficiency improvements without the prospect of gaining market power (Dosi & Nelson, 2010; Romer, 1990). Thus, *temporary* market power and large-scale growth are expected to stimulate competition and innovation, while industry leadership may only be achieved and preserved through lower (quality-adjusted) cost curves. Here, the “invisible hand” operates through a market selection process, which encourages the entry and expansion of the most efficient and innovative agents, the opposite occurring in the case of their less productive counterparts. Capitalist dynamics should then be described as a creative destruction process that fosters production expansion, price reduction, and increased real wages through continuous innovations making obsolete extant technologies, processes, skills, and products (Aghion & Akcigit, 2019). This approach has (partially) allowed the explanation of productive heterogeneity, right-skewed size distributions and firm dynamics, somewhat reconciling theory and evidence.

In that light, the primary objective of this study is to inquire into the long-term stability of creative destruction, testing some of its most critical predictions. Mainly, it analyses the role of transformative entrepreneurship in job creation and resource reallocation and how the industrial lifecycle alters entry and survival regimes. Furthermore, Schumpeterian competition rests on a causal relationship between innovation and market structure and temporary positions of industrial leadership. Therefore, this thesis focuses on the behaviour of dominant companies by inspecting their market share and leadership persistence rate compared to their levels of efficiency and innovation. Lastly, only efficient destruction can guarantee a constant and virtuous creation. The shrinking and bankruptcy of the less efficient firms ensure that resources are reallocated to more productive uses, while market decongestion increases the expected rate of return on any investment. Thus, this study also analyses the selection at the exit margin, intending to investigate which factors may allow an otherwise insolvent firm to survive and the consequences on aggregate efficiency.

At this point, it is worth noting that, albeit the Schumpeterian microeconomic foundations have received relevant support from the empirical evidence, several studies show that market selection is not particularly compelling and that other structural, institutional, and behavioural factors undermine the entry, growth and survival processes (Dosi et al., 2015;

Geroski, 1995). This research, therefore, also benefits from a pluralistic theoretical approach, which allows a critical reading of the capitalist dynamics conceived by Schumpeter and his followers. In that group are, on the one hand, economists linked to the new neoclassical theories of endogenous growth and firm dynamics, among whom Philippe Aghion and Ufuk Akcigit (2019), Daron Acemoglu et al. (2018), Paul Romer (1990), Hugo Hopenhayn (1992), and John Haltiwanger et al. (2013) stand out. On the other hand, we have Schumpeter followers who conceptualise capitalist development as an evolutionary process, characterised by selection and learning, operating in disequilibrium (i.e., the evolutionary approach), led by economists such as Richard Nelson and Sidney Winter (1982a), Giovanni Dosi (1982, 1988), Carlota Perez (2010), Mariana Mazzucato (2013a, 2018), William Lazonick (2016), inter alia.

On the other theoretical shore is Joan Robinson (1953, 1962, 1969), a leader post-Keynesian economist who contributed vastly to technological change and imperfect competition theories, as well as Joseph Stiglitz and Bruce Greenwald (2015), from the neo-Keynesian approach; Paul Geroski (1990, 1995) and Thomas Philippon (2019), from the Industrial Organization literature; Anwar Shaikh (2016), from the classical (Marxist) theory; and, the contemporary economist of Schumpeter and Robinson, Michał Kalecki (1954). This debate across different schools of thought enabled us to draw a much richer set of conclusions while establishing new hypotheses about the relationship between the competitive regime and productivity growth.

This introduction intends to underline in what theoretical and institutional context this research is located. On the one hand, a pluralistic conceptual framework, more than allowing to benefit from cumulative knowledge, sets the dissents from which this research intends to build forward. On the other, institutions play a fundamental role in shaping markets, such that they condition the behaviour of the agents and industries (Acemoglu et al., 2005). The institutional design may, therefore, foster both creative destruction and destructive creation (Mazzucato, 2013a).

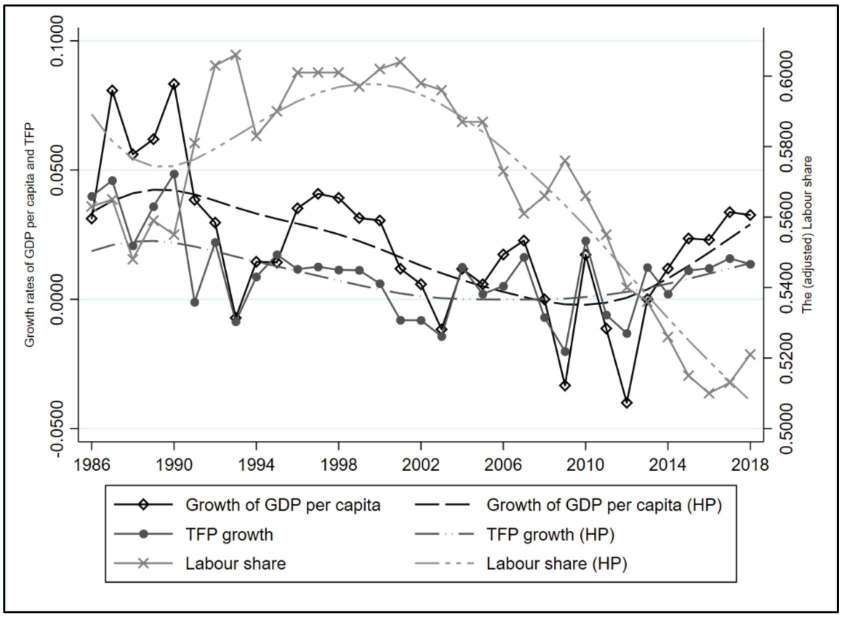
The thesis, in particular, empirically explores the industrial dynamics in Portugal from 1986 to 2018. An increasing body of literature is analysing the factors underlying the phenomenon of productivity stagnation. However, except for the United States (US) literature, most micro-based research has only been based on new-century evidence. Thus, for the first time, this thesis carries out a holistic long-term and economy-wide analysis of industrial dynamics and aggregate productivity growth in a European context. Given the lack of proper extended, longitudinal, micro-level and multisector data, determining the nature of the productivity slowdown is not an easy endeavour. In this case, I assembled a rich longitudinal database that includes the population of companies operating in the manufacturing and service sectors for the entire exploration interval. The sample period enables isolating business cycle effects, thus estimating the structural movements of industrial dynamism. Moreover, this thesis carries out intersectoral analyses disaggregated, in particular, by the knowledge intensity level, therefore intending to capture the different productive trajectories resulting from the emergence of ICT.

Furthermore, although weakening business dynamism, more concentrated markets with old and entrenched leaders, and slowing technological change suggest that creative destruction is running out of steam, economists are far from consensus on its causes. Competing hypotheses range from rising labour and technology costs, higher entry and survival barriers created by dominant companies, increased zombie firms' prevalence, stringent financial constraints, and hindered knowledge diffusion. Analysing and connecting the different long-term trends in industrial dynamics, job creation, distribution, and productivity is therefore critical, as the phenomena are interdependent and the competitive regime is not static. Moreover, this analysis benefits from the evolutionary insights of technological paradigms and industry lifecycle since the dynamics of creation, destruction and value extraction likely mirror the mutation of the new paradigm linked to the ICT revolution.

The Portuguese case provides the necessary scenario to address the abovementioned issues. On the one hand, Portugal shares much of the macroeconomic pathology of the other industrialised countries. The Portuguese economy has seen robust economic expansion during the last two decades of the 20th century, as shown in Figure 1.1. However, output and productivity growth rates have remained stagnant since 2000, while the labour share has fallen more than eight percentage points between 2000 and 2018.[1] This phenomenon has been exacerbated by the counter-productive destruction that occurred during the 2008-2013 Portuguese crisis (Carreira et al., 2021).

[1] The official statistics were taken from the annual macro-economic database of the European Commission (AMECO) (Information available at AMECO Online - AMECO Online (Current Version 2022-11-11 11:00) | Pasta - Qlik Sense (europa.eu))

Figure 1.1 GDP and TFP growth rates and the Labour Share in Portugal over 1986-2018



Source: AMECO. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Own computations.

On the other hand, despite preserving many of the institutions established with the "Carnation Revolution" of 1974, the Portuguese economy has also suffered significant liberal reforms, especially from its entry into the European Union (EU). These reforms are characterised by the privatisation of public enterprises, financial deregulation and labour market flexibility, to mention a few aspects. The Organisation for Economic Co-operation and Development (OECD), for example, reports that the Product Market Regulation Index decreased from 2.59 in 1998 to 1.34 in 2018.[2] Likewise, the Employment Protection Index (IPE) of regular workers fell from 5 in 1985 to 3.14 in 2018, while that of temporary workers was reduced from 3.38 in 1985 to 1.94 in 2018.[3] Furthermore, according to the International Labour Organization (ILO), the union density rate decreased from 21.6% in 2000 to 15.3% in 2016.[4] Finally, according to the "Financial Freedom" component of the Economic Freedom Index published by "The Heritage Foundation", the Portuguese financial market

[2] This index which measures the degree of government control and regulatory barriers for entrepreneurship, international trade and investment (Information available at Indicators of Product Market Regulation - OECD).

[3] These indexes evaluate the degree of regulation of individual and collective layoffs (Information available at OECD Indicators of Employment Protection - OECD).

[4] (Information available at ILO Data Explorer).

would have switched from "considerable" government interference to "moderate" interference during the first two decades of the new century.[5]

1.2 Organization of the thesis

This thesis is organised into nine chapters, where the main contributions are developed in the fifth, sixth and seventh chapters.

Chapter 2 briefly discusses the agreements and dissents across the different theoretical approaches regarding the relationship between competition and technical progress. Given the empirical failure of perfect competition and exogenous technological change, creative destruction seems to be the proper benchmark of a competitive economy. Therefore, this chapter seeks to identify its main characteristics and underlying assumptions and then confronts the criticism generated from the other schools of thought. The chapter then presents the evidence on firm dynamics, market structure and productivity growth.

Chapter 3 discusses the productivity slowdown observed in the new century. First, it documents empirical stylised facts on declining business dynamism and increasing market concentration. Second, it discusses the competing theories that attempt to explain these trends, dividing them into two major groups: "good concentration" and "bad concentration" (i.e., Schumpeterian and non-Schumpeterian concentration). In particular, the "good concentration" hypotheses suggest that enhanced information flow to consumers and a greater preponderance of intangible capital gave highly productive firms a superior and difficult-to-imitate competitive advantage, thus causing efficient accumulation and productivity growth but discouraging would-be innovators in the long run (Aghion, Bergeaud, et al., 2022a; Autor et al., 2017). The "bad concentration" theories, in turn, point to increased barriers to competition, expressed in hindered knowledge diffusion, higher technology costs and increasing financial constraints, mergers and acquisitions, predatory practices, and higher lobbying spending by dominant firms, stimulated by "rent-seeking" behaviour and facilitated by a favourable regulatory setting for large corporations (Lambert, 2019; Philippon, 2019; Reich, 2015; Stiglitz, 2019). Third, it presents Covarrubias et al.'s (2020) competitive selection model to shed light on this debate while raising the main hypotheses. This thesis particularly conjectures that productivity stagnation is an increasing

[5] This index measures the degree of regulation of financial services, the state's proprietary control over banks and financial companies, the government influence in the allocation of credit, the degree of openness to foreign competition, and the level of development of financial markets (Information available at Index of Economic Freedom: Promoting Economic Opportunity and Prosperity by Country (heritage.org)).

function of non-Schumpeterian market selection. I define non-Schumpeterian selection as the process that enables firm entry, expansion and survival through determinants other than efficiency and innovation. This type of selection may occur due to increasing mobility barriers (or barriers to competition in Covarrubias et al.'s (2020) model). Thus, a non-Schumpeterian selection is expected to undermine technical progress because it impairs allocative efficiency and weakens the incentives to generate or adopt new technologies. This thesis also hypothesizes that creative destruction most likely dominates in the ascending phase of the technological paradigm. However, the opposite is expected in its downswing, where mobility barriers are likely to prevail.

Chapter 4 is divided into dataset construction and productivity measurement sections. This research uses three sources of information: *Quadros de Pessoal* (QP), *Ficheiro das Unidades Estatísticas* (FUE), and *Sistema de Contas Integradas das Empresas* (SCIE). QP is a longitudinal dataset annually gathered from 1985, covering the population of firms operating in all sectors.[6] Instead, FUE and SCIE were collected during 1996-2004 and 2004-2018, respectively, and comprise the universe of corporations. Since four industrial classification methodologies have been in place, I have performed a homogenisation process to build time-consistent industry codes, then keeping only the manufacturing and non-financial market services sectors. As a result, the final sample comprises an unbalanced panel of 896,827 enterprises, totalling 7,534,119 year-firm observations (including new, continuing, and exiting firms). Moreover, this thesis uses labour productivity and total factor productivity (TFP) as firm efficiency measures. Chapter 4's second section explains their estimation process and underlying assumptions.

Chapter 5, through a long-term analysis of the Hodrick-Prescott (HP) filtered trends, focuses on the entry and exit rates, post-entry survival and growth-rate distribution dynamics and job reallocation. Here, it is critical to note that more vigorous growth generally implies higher turnover rates of firms and labour, generated by the required creative destruction process (Aghion & Akcigit, 2019; Dosi & Nelson, 2010). In turn, its long-term dynamic properties critically depend on a permanent entry of high-productivity start-ups, expected to offset job losses resulting from the early death of weaker firms in their cohort, stimulate frontier firms' innovation and prevent monopolies' entrenchment. Accordingly, Chapter 5 explores the long-run behaviour of this process aimed at keeping competition, net job

[6] Except for the domestic services sector.

creation and technical progress in constant operation. The results show a structural change in business dynamism since 2000. The pre-2000 period was characterised by intense creative destruction, mainly driven by expanding knowledge-intensive activities. Job reallocation increased while start-ups and young firms played a leading role in net job creation. Nevertheless, the entry of new competitors and their share in net job creation significantly fell during 2000-2018, while job reallocation markedly declined. In addition, although high-growth young firms showed a better performance throughout the 1990-2018 interval, they did not offset a lower entry and survival. As a result, new and young firms reduced their share in net job creation and aggregate employment.

Chapter 6 is divided into two sections. The first section estimates structural trends (HP) on the evolution of the competitive regime—in terms of market share instability index, concentration ratios, and leadership persistence rate—compared with efficiency and innovation gaps between leaders and followers. The evidence indicates that, from the beginning of the new century, the average Portuguese industry moved from a Schumpeterian concentration scenario to a non-Schumpeterian one (i.e., a market structure not entirely driven by efficiency and innovation differentials), particularly in the industries that presumably emerged with the ICT paradigm. Thus, the typical industry has exhibited a higher concentration rate, a greater likelihood of preserving dominant positions, and lower market share instability. Furthermore, the study found that the technology gap between leaders and followers has widened while the innovation gap has almost vanished, suggesting that industry leaders have been able to expand their market share and preserve their dominant positions with smaller innovative efforts (both leaders and followers exhibit industry-average productivity growth rates by 2018).

The second section of Chapter 6 tests a key hypothesis of this research, namely whether "non-Schumpeterian concentration" is possible due to "Schumpeterian concentration". This finding entails a vital dilemma I called 'the paradox of Schumpeterian competition,' since *competition tends to (Schumpeterian) concentration, and then concentration results in a weaker competition*. Specifically, industry-level regression results indicate that leaders preserve their dominant positions more easily in industries with a higher concentration rate. At the same time, the greater the leadership persistence, the lower the market share instability. Subsequently, estimates show that dominant firms have diminished incentives to innovate in deteriorated competitive settings (i.e., with weak market instability and high concentration). Lastly, firm-level fixed effects panel regressions indicate that the higher the industrial concentration, the smaller the effect of the company's productivity growth on market share expansion, that is, the central Schumpeterian competition outcome.

Chapter 7 is devoted to studying unprofitable and highly indebted companies (i.e., zombie firms), focusing on their incidence in the Portuguese economy and the determinants that allow their survival. As a central aspect, this chapter empirically assesses whether the 2012 reforms in the Portuguese insolvency framework, especially the policies aimed at improving the efficiency of prudential banking supervision and insolvency legislation, reduced zombie survival. First, this inquiry uses treatment effect and multinomial logistic estimators to examine whether the implemented reforms contributed to reducing zombie entrenchment efficiently. Next, it performs fixed effect panel regressions to assess whether the institutional changes were associated with a higher productivity-enhancing reallocation. The results show a significant incidence of zombie firms during the new century, and that industries with a higher share of zombies exhibit lower productivity levels. Afterwards, the main findings suggest that the new (more debtor-friendly) institutional framework was directly responsible for reducing zombie entrenchment. Yet, although reallocation barriers as a whole are reduced after the reforms, they seem to have a more significant effect on the recovery than on the exit transition. In addition, and more importantly, the most productive firms have an increased recovery probability in the post-reform period. The results further confirm that firm size plays a crucial role in insolvency. Accordingly, the reforms make the restructuring transition more likely in companies characterised by complex ownership and debt structures, as well as in those typically prone to liquidation due to a high share of concentrated and secured debt. Finally, the estimates indicate that the decline in entrenchment barriers is also associated with lower economy-wide distortion in selection and reallocation.

Chapter 8 presents the conclusions, connecting and analysing all the results and long-term creative destruction trends. This study shows a structural change in industrial dynamics beginning in 2000. On the one hand, in line with Schumpeter's postulates, the results suggest that the Portuguese economy has shown intense creative destruction in the pre-2000 interval, particularly in the knowledge-intensive industries. But, on the other hand, creative destruction seems to have deteriorated since 2000. This fact is expressed in declining entrepreneurship and reallocation, increasing concentration, and higher exit barriers. This dynamic is very similar to that reported by other studies for the US case, and it is here that the interpretive differences emerge most visibly. Under Covarrubias et al.'s model (2020), if the enhanced information flow and the intangible capital deepening were to explain the long-term patterns, the higher market concentration rate should have been accompanied by an increase in investment, the productivity of incumbent firms, market share instability, leadership turnover, and exit hazard. Nonetheless, the thesis findings depict the opposite picture. The non-Schumpeterian concentration and the exit barrier intensification appear to best explain the productivity slowdown in Portugal. As a result, the post-2000 Portuguese industrial dynamics seem to support *bad* concentration theories and, mainly, the central proposition of this thesis: productivity stagnation is an increasing function of non-Schumpeterian market selection. *Chapter 8* also contains a few closing thoughts on the public policy implications, as well as some notes on future avenues for research.

2 Competition, innovation, and market structure

The analysis of industrial dynamics has gained particular relevance in the new neoclassical theories of endogenous growth (Acemoglu et al., 2018; Aghion & Akcigit, 2019) and labour market functioning (Card et al., 2018; Lentz & Mortensen, 2010). These models have incorporated many of Schumpeter's claims (1934, 1942), an author who significantly changed our understanding of competition and innovation long ago. This perspective has also been embraced by the evolutionary (Dosi & Nelson, 2010) and post-Keynesian (Lavoie, 2014) economic schools, as well as by the industrial organisation literature (Carlton & Perloff, 2015).

Since real markets are characterised by information costs and asymmetries, agent heterogeneity, structural uncertainty and bounded rationality, and endogenous technological change, innovation is expected to drive business dynamism, market structure, economic growth, and income distribution. In such a context, the continuous replacement of obsolete and less efficient ideas and technologies with new and more creative ones is expected to be the hallmark of development.

Although there is still no consensus on which factors determine productivity, what is new and what is obsolete and whether free markets encourage creative destruction, most approaches now acknowledge that firms, in practice, have a long-term perspective and do not play a passive, price- and cost-taker role. Instead, they use technical progress as the primary device to maximise long-run profits (Aghion & Akcigit, 2019; Dosi & Nelson, 2010; Lavoie, 2014; Shaikh, 2016; Stiglitz & Greenwald, 2015). Those more innovative see their market share and profitability increase—eventually becoming industry leaders—while the opposite is expected to occur for their less efficient counterparts. Higher costs and inferior quality cause a loss of consumers, more significant restrictions on obtaining financing, and enormous difficulties in competing in labour markets, reaching the point where bankruptcy is imminent. A low-productivity firm is likely to retain its (small) industrial share in the short term by adjusting its profit margin. However, only the generation or adoption of better practices would enable survival or growth in the medium and long term. Therefore, the primary capitalist regulatory mechanism lies in market selection, with aggregate productivity fuelled both by the innovations and investments carried out by entrants and incumbent firms and the resource reallocation towards more efficient uses.

These theoretical predictions have received much attention over the past decades, and the empirical evidence seems to support them (see Dosi & Nelson, 2010; and Syverson, 2011 for a survey). Nevertheless, several studies have also shown that selection in practice is not compelling (Bottazzi et al., 2010; Dosi et al., 2015). Other variables, structural, institutional and behavioural, undermine the *efficiency* and *justice* of competition. Since many opposing forces influence market outcomes simultaneously, understanding capitalism is only possible when analysing its long-term path. Some forces push for growth and innovation, while others enable selection forces to be circumvented, thus facilitating an accumulation sans investment. The institutional setting (including deregulation) plays a critical role in shaping the trajectory of an economy, which may encourage 'creative destruction' or, instead, 'destructive creation' (Mazzucato, 2013b).

2.1 An overview of competing theoretical approaches

2.1.1 From perfect competition to creative destruction

The analysis of industrial concentration requires an understanding of competition and the factors underlying the formation of market structures. However, in a standard perfect competition scheme—with symmetric costs, homogeneous products, perfect and complete information, diseconomies of scale, small optimal size, and, ergo, exogenous prices—competition, concentration and market power are unable to coexist. Productivity heterogeneity and highly right-skewed size distributions, pervasive in the empirical literature (Dosi & Nelson, 2010; Syverson, 2011), thus suggest that the Arrow-Debreu (1954) conditions have been broken or that it is required to change the analytical framework to understand what a competitive economy actually means. This aspect becomes essential in light of a systematic increase in industrial concentration and market power in most developed economies during the new century (De Loecker & Eeckhout, 2018).

The bulk of the empirical record reveals that, even in narrowly defined industries, quite a few large corporations cohabit with a vast spectrum of relatively small firms (Bottazzi et al., 2007; Dosi, 2007). As a result, imperfect or oligopolistic competition at any given time seems to describe better the process of price formation and market share allocation. Robinson (1932) and Chamberlin (1933) were pioneers in providing rationality and formalism to the imperfect markets theory. However, all the possible equilibria in these theoretical paradigms yield presumably suboptimal efficiency outcomes. Indeed, one of the main conclusions of the seminal Dixit-Stiglitz (1977) model of monopolistic competition indicates that markets with differentiated products—where each producer faces a downward-sloping demand curve—are characterised by a constrained Pareto optimal solution. As other 'market failures' intensify, equilibria become sub-optimal (Stiglitz, 2017). In oligopoly theory, except for competition *à la Bertrand* with homogeneous products, all strategic interactions result in a deadweight loss (Carlton & Perloff, 2015).

For Schumpeter (1942), however, the *static inefficiency* of markets is a necessary condition for innovation and the maximisation of *dynamic efficiency*. Innovation and entrepreneurship entail fixed (or even sunk) costs and increasing returns. Thus, the company's operation ceases to be profitable under perfect competition. The (quasi) rents derived from an imperfect market are expected to be the reward that firms receive for innovating in an eminently uncertain environment. Schumpeter, therefore, considered that more than being unfeasible, perfect competition was inferior (see Lazonick, 2020 for an extension).

Capitalist dynamics ought to be described as a process of creative destruction—led by a front group of innovators and their respective squadron of active imitators—, which would encourage the expansion of production, the reduction of prices, and the rise of real wages through continual innovations that render obsolete technologies, processes, skills, and products (thus, also markets or sectors) that existed until then (Aghion & Akcigit, 2019).[7] According to Schumpeter (1942), market power and large-scale growth drive innovation, with 'market competition' being replaced by 'competition for the market' (Schumpeterian competition henceforth) (see also Nelson & Winter, 1982a). The competitive pressure, current (i.e., incumbents) and potential (i.e., entrants), would, in turn, limit the dominant corporations' market power. In such a setting, firm dynamics and market structure must be functions of relative efficiency and innovation. At the same time, aggregate productivity would benefit from within-firm innovations and efficient resource reallocation. Therefore, industrial concentration is not necessarily bad news in a market economy driven by creative destruction—especially for the Schumpeter (1942) of "Capitalism, Socialism and Democracy" and his later followers (Futia, 1980; Nelson & Winter, 1982b). There is a causal relationship between innovation and market power, and critical mass agglomeration,

[7] This dynamic is expected to also allow wages to keep in line with productivity. In this regard, one of the main criticisms of Schumpeter (1942) to Marx (1867) relied on a stable labour share that several western economies had experienced between the 19th century and the beginning of the 20th century, as this fact differed from the downward trend that Marx had predicted. Schumpeter argued that one of the main flaws in Marx's analysis was to overlook profit-making through (quasi) rents derived from an imperfect product market.

economies of scale and greater financing availability of large firms—in imperfect capital markets—are expected to nurture more innovation.

Despite their noticeable differences, the evolutionary theory (Dosi & Nelson, 2010; Nelson & Winter, 1982a) and the new neoclassical theories of endogenous growth (Aghion et al., 2001; Romer, 1990) and industrial dynamics (Hopenhayn, 1992; Jovanovic, 1982) have internalised the Schumpeterian theses of competition and technological change. As Romer (1990) points out, much of the technical progress has resulted from innovations within the production units. However, knowledge is an input independent of human capital and differs from a pure private good because it is non-rival. As a result, the production possibility set exhibits non-convexities, and a price equal to marginal cost becomes unsustainable. The tacit nature of knowledge,[8] intellectual property protection, and information and transportation costs allow innovators to enjoy (temporary) monopoly power. However, even with patent protection, knowledge spill overs (i.e., it is a partially excludable good), and a firm tends to underinvest in equilibrium (Aghion & Akcigit, 2019; Romer, 1990).[9] Lastly, the free entry condition and the corresponding expected net present value equal to zero ensures that what has been created is destroyed and that the monopoly is temporary.

Romer's (1990) endogenous growth model is a handy analytical tool for understanding the determinants of technological progress. Nevertheless, since it is based on a Dixit-Stiglitz monopolistic scheme, the importance of competition is given exclusively by the product variety (and the intensity of substitution), each one representing a market. Consequently, it is unable to internalise the reallocation effect on productivity growth and explain the industrial structure (with products whose cross elasticities are high) and firm dynamics.

Aghion et al. (2001) instead developed a Schumpeterian growth model where a Bertrand duopoly with asymmetric costs and differentiated products characterises each industry. The main features of the model may be described as follows. If q_A and q_B denote the two firms' output, and α measures the degree of substitutability between the two products,[10] the production of industry j is derived as follows:

$$f(q_A, q_B) = \left(q_{Aj}^{\alpha} + q_{Bj}^{\alpha}\right)^{1/\alpha}, \alpha \in (0,1]. \tag{2.1}$$

[8] That is, the inability of competitors to immediately replicate a given innovation.

[9] Additionally, not all innovations can be patentable, especially when they are incremental or organisational.

[10] We can imagine that the degree of substitution depends both on product differentiation and on search and transportation costs.

Next, let us denote c_A and c_B as the unit production costs of each firm, and assume that, after consumers' choice, the elasticity of demand faced by each firm i is given by $\eta_i = (1-\alpha\lambda_i)/(1-\alpha)$, where $\lambda_i = p_i q_i$ is the firm revenue. Then, the profit π_i and price p_i functions of each firm in Bertrand equilibrium is given by:

$$\pi_i = \frac{\lambda_i}{\eta_i} = \frac{\lambda_i(1-\alpha)}{1-\alpha\lambda_i},\ i = A, B \tag{2.2}$$

$$p_i = \frac{\eta_i}{\eta_i - 1} c_i = \frac{1-\alpha\lambda_i}{\alpha(1-\lambda_i)} c_i,\ i = A, B \tag{2.3}$$

where,

$$\lambda_i = \frac{p_i^{\alpha/\alpha-1}}{p_A^{\alpha/\alpha-1} + p_B^{\alpha/\alpha-1}},\ i = A, B \tag{2.4}$$

In this Bertrand setting, given the elasticity of substitution among producers α (which measures the degree of competition), the profit ϕ_i of each firm is determined by its relative cost $z_i = c_i/c_{-i}$ since cost reductions proportionally translate into price cuts. Therefore, the firm with the leading-edge technology is expected to capture the largest market share and enjoy a higher profit margin.[11] Finally, this formulation allows the follower to challenge market leadership in the future, for which it must 'step by step' catch up with the current technological leader.

According to Aghion et al.'s (2001) model, when $z_i = z_{-i}$, for a given elasticity $\alpha > 0$, rivalry becomes 'neck and neck,' and firms have the incentive to innovate to *escape competition*. Consequently, the larger the α, the more intense the firms' effort to technologically outperform their rivals. Instead, when α approaches zero, the market structure becomes independent of relative costs, and the incentive to innovate vanishes. On the other hand, when the technological gap between the leader and the follower is vast (i.e., with many steps), a significant increase in α diminishes innovation incentives in both firms—the leader is already earning the maximum possible profit, and the follower's catching-up turns out to be too expensive. Lastly, when $z_i > z_{-i}$ and $\alpha = 1$, the game evolves to a Bertrand competition with asymmetric costs and homogeneous products, whereby the "*winner takes all*" (i.e., the leader i) fixing a price equal to the marginal cost of

[11] A similar market share allocation can be obtained in a Bertrand competition with asymmetric costs and capacity constraints, as well as in any Cournot competition with asymmetric costs.

the follower $-i$.[12] The authors finally suggest that some imitation is always positive because it stimulates closer competition, whereas too much imitation threatens appropriation and thus discourages innovation.

Dynamic competitive selection models offer interesting alternative explanations that also rely on Schumpeterian premises (Hopenhayn, 1992; Jovanovic, 1982). In these schemes, the productivity distribution largely explains the market share distribution. In addition, a minimum efficiency threshold from which the operation ceases to be profitable determines entry and exit. The productivity distribution is therefore left truncated. Capacity constraints (due to the profit function's concavity), in turn, prevent the technology leader from serving the entire market (Syverson, 2011).

Evolutionary models depend on different theoretical assumptions—in a system that operates in *disequilibrium*. Nevertheless, the Schumpeterian corollaries of technical progress hold: production growth is fuelled by continuous innovation and imitation; (temporary) monopoly rents stimulate innovation; and creative destruction guides capitalist dynamics (Dosi & Nelson, 2010). Here, Schumpeterian competitive selection is characterised by "replicator dynamics" that adopts the following representation:

$$\Delta \mathrm{s}_{\mathrm{i,t}} = f\left(\omega_{i,t} - \bar{\Omega}\right) s_{i,t-1}, \tag{2.2}$$

where $s_{i,t}$ denotes the market share of the firm i in period t, $\omega_{i,t}$ the firm productivity and $\bar{\Omega}$ the industry's average productivity. Since competitiveness is inversely proportional to prices, which are inversely proportional to productivity (costs), this formulation assumes that, conditional on initial size, companies with above-average productivities exhibit relatively higher growth and expand their market share, occurring the opposite in their less efficient counterparts.[13]

In the evolutionary approach, business growth depends on the ability to charge lower prices and thus attract more consumers. Hence, the strategic variable is not the price (as in Bertrand) or the quantity (in Cournot) but the technology. Therefore, the evolutionary competitive

[12] This model abstracts from the role of business entry. However, Aghion et al. (2001) suggest that a higher entry would enhance the effect of competition on innovation. Acemoglu et al. (2018) provide a slightly more sophisticated model's variant, which includes entry and exit dynamics. However, the results regarding the incentives for innovation and the determination of the industrial structure are qualitatively comparable.

[13] Harmonizing evolutionary competitive selection with the Aghion et al.'s (2001) scheme, the replicator dynamics can be expressed as follows: $\Delta s_{i,t} = f\left(\frac{c_i}{c_{-i}}\right) s_{i,t-1}$. Therefore, under the same reasoning, companies with lower relative costs are expected to increase their market share.

selection is similar to Shaikh's (2016) 'real competition' scheme. According to Shaikh (2016), in real competition, firms struggle to attract consumers—from other companies and other markets—, expand their industrial share and maximise their long-term profit, using price as their *weapon* and advertising as their *propaganda*. Cost reduction becomes a critical concern, as prices are ultimately cost-constrained. Costs depend on the working day's length and intensity, the wages paid to workers, and the technology used. However, technical progress is the primary cost-reduction mechanism in the long run. The technology is not chosen based on the profit rate but on the unit operating cost since such a choice imposes greater losses on its competitors and therefore increases future profits. The battle among companies determines the industry's *regulating capital*, corresponding to the one with the lowest reproducible costs (adjusted for quality). Based on regulating capital, asymmetric profit margins are set, as real competition tends to *"disequalise profit margins and profit rates precisely because it tends to equalise selling prices."* (Shaikh, 2016, p. 262)

We should note that market shares are essentially exogenously determined in all these theoretical approaches.[14] Also, except for the possibility of unilaterally cutting wage rates—in imperfect labour markets—of the Shaikh (2016) scheme, market expansion and business profit are always the reward for value creation (derived from technical progress). Competitive pressure compels companies to improve their relative cost position to grow, increase their unit margins, and, thus, raise their expected profit.[15] Consequently, one of the critical aspects of fostering long-term creative destruction is ensuring that competitive pressure never fades.

2.1.2 Controversies over creative destruction

A long time ago, Arrow (1962) challenged the corollary that suggests that market power is always the cost society must bear to reward innovation and favour its flourishing. Arrow (1962) posits that if ϕ and ϕ' denote monopoly profits before and after a given innovation, the current monopolist's incentive to innovate is $\phi' - \phi$, whereas that of the would-be innovator is ϕ'. In other words, the opportunity cost of innovating for a firm whose monopoly rents are based on previous innovations is higher than that of potential innovators.

[14] Although in a Cournot competition firms determine quantities, their choice is limited by demand conditions, relative cost ratios, and the simultaneous and independent choices of their competitors.

[15] It is worth noting that Shaikh claims that there is no market power, because "*Real competition is the central regulating mechanism of capitalism*" (Shaikh, 2016, p. 259). He further suggests that the adoption of a 'markup' necessarily forces one to think that perfect competition exists and, therefore, any different price would indicate a departure from this paradigm, which is for him (as well as for Schumpeter) illusory.

This presumption is because the innovation net return of an established monopolist is diminished by the displacement of productive activities anchored to the old technology. Thus, Arrow famously postulated that *"[...] The preinvention monopoly power acts as a strong disincentive to further innovation"* (Arrow, 1962, p. 620).

In a modified formulation of the "Arrow replacement effect," Holmes et al. (2012) add that adopting new technologies entails *switchover disruptions* resulting from a temporary sales reduction in technologically displaced units. The greater the switchover disruptions, the higher the opportunity cost. A larger monopoly power implies a higher opportunity cost of continuing to innovate and, therefore, a more entrenched conservative position.[16] Moreover, it is widely accepted that risk is directly proportional to the innovation novelty. Then, a higher risk entails a higher opportunity cost to continue innovating, so a large monopoly has less incentive to participate in over-risky Research and Development (R&D) projects (Dasgupta & Stiglitz, 1980).

It must be highlighted that creative destruction critically depends on a limited temporality of dominant positions. Although Schumpeter (1942) disapproved of the entrenchment of monopolies, he assumed that new innovators would always emerge to displace market leaders. However, Stiglitz and Greenwald (2015) precisely argue that one of the main flaws of Schumpeter's thesis lies in underestimating the persistence ability of dominant firms. In Schumpeterian models, both neoclassical and evolutionary, it is assumed that the unique response of leading companies in the face of any external threat is to undertake more innovation. Nevertheless, if the opportunity cost of further innovating increases with market power, dominant firms may be tempted to defend their position through strategic behaviour, provided that the corresponding net return is greater than that of developing or incorporating new technologies.

Geroski et al. (1985) and Geroski and Toker (1996) suggest that industry structures would be rather rigid, with larger, top-ranked firms able to hold their position longer than their smaller rivals. Moreover, the authors stress that leaders' persistence depends not so much on what they are (i.e., large companies) but on the strategic advantage that accumulation confers them to discourage the entry and growth of their rivals (e.g., via advertising or limit pricing),

[16] On the other hand, Aghion et al. (2001) suggest that inertial behaviour can also be the result of a very wide technology gap in a market with highly elastic cross-demand, since it reduces the expected return of the follower's catching-up.

achieve pre-emptive mergers and acquisitions,[17] obtain financing and, of course, innovate.[18] Still, when industries reach a certain degree of maturity, economies of scale play a critical role, thus discouraging the deployment of potential competitors (Geroski, 1995). On the other hand, it is well-known that the cartel's success depends heavily on the number of participants and monitoring costs. Therefore, more concentrated markets favour the stability of cartels (Levenstein & Suslow, 2006).

Stiglitz (2018) further claims that modern dominant firms allocate vast resources to raise "innovative" entry and mobility barriers that enable them to expand their market power. Moreover, the use and management of Big Data impose new fixed costs on infant firms while allowing large companies to influence demand elasticities. Network externalities can also arise exogenously and endogenously in ICT-intensive markets, reinforcing the market power of dominant firms. Finally, since expensive technologies characterise modern industries, sunk entry costs are more relevant. As a result, leading firms may invest just enough in R&D to convince potential innovators that they would lose if they entered the race (Stiglitz, 2018).

Robinson (1969), despite overlooking the role of reallocation, also hypothesised a model of long-term accumulation in which technical progress is continuously fuelled by technological leaders and followers who are compelled to innovate or imitate in response to competitive pressure. In this approach, the equivalent of creative destruction is what she calls the *Golden Age of Capitalism*, characterised by a downward price trend and a constant productivity-to-real wage ratio.[19] Nonetheless, Robinson warns that preserving the system's stability becomes very precarious under pure capitalist rules of the game. She postulates that the system breaks down fundamentally in four situations: "(1) the rate of technical progress alters unexpectedly; (2) the competitive mechanism becomes clogged; (3) accumulation tends to vary relatively to the rate of increase of productivity; (4) technical progress fails to be spread evenly throughout the system" (Robinson, 1969, p. 89).

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[17] In this regard, extensive theoretical and empirical literature suggests that the potential efficiency gains due to mergers have been generally overestimated.

[18] Geroski (1990) further suggests that as long as the future outcomes of a given innovation complement the technology the monopolist is currently enjoying, the monopolist is expected to have a higher reward for its introduction and, if necessary, will pre-empt rivals.

[19] 'Progressive' entrepreneurs (i.e., those who innovate or introduce leading-edge technology first) can cut prices to attract more consumers and raise wage rates to hire more and better labour. Followers have to do the same until the old technology no longer yields 'quasi-rents.' At that point, they must (at least) imitate the technology or exit the market (Robinson, 1969).

Robinson (1969) argued that an immediate effect of suddenly altering the pace of technical progress is to lengthen the profitable life of old-fashioned capital, thus discouraging new investment. In turn, this would lead to a labour surplus (i.e., structural unemployment) and, consequently, insufficient aggregate demand. As a result, the economy is expected to enter a long stagnation period.

Regarding the second cause, it is important to highlight that the 'mature' version of the 'Robinsonian imperfect competition' (1953) has many similarities with the Schumpeterian competition (via innovation and imitation). However, Robinson points out that competition tends to weaken as time goes by since large companies acquire more persistence through non-competitive mechanisms. Their entrenchment would be determined endogenously and exogenously. On the one hand, accumulation allows them to discourage their rivals' entry and growth, mainly through advertising and predatory pricing (Robinson, 1953). On the other hand, larger economies of scale and increasingly rationed credit markets enable dominant firms to enjoy a quiet life. Since initial assets and retained earnings would chiefly condition investment (and access to finance), she considered, like Kalecki, that imperfect capital markets facilitate greater concentration, which in turn affects income distribution and the adoption of new technologies (Kalecki, 1954; Robinson, 1962).

Given the empirical evidence and advances in theories on the finance provision under asymmetric information and structural uncertainty, there is little doubt about the rationed feature of credit markets (Carreira & Silva, 2010; Stiglitz & Weiss, 1981). Nonetheless, just as product-market imperfections would leverage innovation and entrepreneurship, some evolutionary authors suggest that investment-cash flow sensitivities strengthen competitive selection since they enable the most productive companies to invest and grow at a higher rate (Coad, 2010). If most productive firms have above-average financial returns, and demand agents use retained earnings to 'signal' efficiency (or co-invest), a *replicator dynamic* is also expected to operate in credit markets favouring productive assets growth of technologically superior firms. Thus, financial constraints are likely to prevent the expansion of inefficient firms and facilitate efficient resource reallocation (Coad, 2010; Nelson & Winter, 1982a).

Nevertheless, as Coad (2010) also points out, financial restrictions seem to be really important for new and young enterprises. A potential entrant has not yet 'proven his worth' and thus cannot signal his ideas' merit. Consequently, as Kalecki (1954) suggested, the most crucial variable would be the 'entrepreneurial capital' and its subsequent reproduction. In addition, given the increasing risk, retained earnings are not the unique determinant of access to finance but also potentially collateralised assets. On the other hand, not all the economic agents that give life to a new product or market are 'true entrepreneurs' since many projects may be promoted by deep-pocket corporations that dominate other markets (Robinson, 1953). Lastly, the relationship between initial assets and investment (and the underlying incentives) is likely to be critically mediated by the risk inherent in the business cycle (Minsky, 1986).

Let us now consider the pace of the generation and diffusion of knowledge and technology, where the evolutionary school likely has more to say. Dosi (1988) states that innovation involves a 'problem-solving' situation. The solution to a technological problem requires, in turn, the use of information drawn from a previously consolidated *knowledge base* (which includes both public and tacit or specific knowledge). The knowledge base outlines the information and skills that inventors use when searching for innovations (Nelson & Winter, 1982a). This knowledge base is ultimately bounded by what the evolutionary school designates as *technological paradigms* (which resemble the long-term innovation waves of Schumpeter (Schumpeter, 1939)), defined as "*the cognitive frames shared by technological professionals in a field that orient what they think they can do to advance a technology*" (Dosi & Nelson, 2010, p. 67). In other words, each technological paradigm embodies the *technology of technical change*.[20]

According to Robinson (1969), exhaustion of inventiveness, a slowdown in knowledge diffusion, and distended competitive pressure (i.e., slackened incentive to innovate) undermine technological change. But, since the prevailing paradigm constrains technical progress, a dried-up of inventiveness likely reflects that the usually *dynamic increasing returns* entered a declining phase—until the emergence of a new paradigm (Nelson, 2008; Perez, 2010). That is, knowledge production is probably operating on the *technological paradigm's possibilities frontier*. Consequently, the rates of arrival and return of a given invention would not depend exclusively on innovative efforts (and investment in R&D) but also on the exploitation degree of the technological paradigm. Furthermore, since the knowledge base—from which innovators carry out search processes—is nourished by the discoveries and inventions made in the past, hindering the knowledge diffusion flow, in

[20] Examples of such technological paradigms include the internal combustion engine, oil-based synthetic chemistry, and semiconductors (Dosi, 1988).

addition to undercutting the catching-up of followers, is expected to impair the generation of new knowledge (Dosi & Nelson, 2010).

The conventional wisdom that stronger and broader patent regimes are essential for technological change seems then ill-conceived. Furthermore, while there is little doubt that the private incentive to innovate is likely to dissipate without protection, scholars such as Dosi et al. (2006) argue that, above a minimum threshold, there is no monotonic relationship between appropriability and propensity to innovate.[21] So, excessive patenting could trigger what Heller and Eisenberg (1998) called the 'tragedy of the anticommons,' where excessive fragmentation of Intellectual Property Rights (IPRs) would hold back research activity because all would block each other. Stiglitz and Greenwald (2015) agree with this argument, highlighting that a stronger, especially poorly designed, IPRs regime reduces the pool of knowledge, thus diminishing research opportunities. The authors further argue that institutional settings that overprotect knowledge and induce strategic use of IPRs facilitate monopolies' entrenchment.

In the Robinsonian scheme, knowledge diffusion also critically depends on the patent system and trade secrets.[22] Nevertheless, Robinson (1962) held that higher technology costs and increasing financial constraints would further impair long-term imitation and innovation processes for *progressive* entrepreneurs. However, a dominant firm *overprotected* by IPRs is likely less threatened by potential competition. At the same time, knowledge diffusion is expected to be shallow in a depressed competitive environment. In other words, the four causes of the slowdown of technical progress, suggested by Robinson (1969), are very likely to be interrelated.

Finally, it is worth noting that although Shaikh's (2016) real competition framework has similarities with Schumpeter's competition paradigm, it does not mean that, for the author, *laissez-faire* capitalism is capable of reproducing an economic and productive evolution under the standards of creative destruction. On the one hand, Shaikh (2016) argues that real

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[21] Dosi and Nelson (2010) also point out that, in many cases, the time and decoding effort required to build productive and organizational capacities to implement new technologies allow returns to R&D to be high, even when patents are weak. Hence, imitation, even without IPRs, is not free.

[22] She argued that the absence of intellectual property would discourage innovative activities since investment could not be amortised without a minimum level of quasi-rents. Therefore, it is necessary to slow down the dissemination of knowledge so that more knowledge can be disseminated in the future. Lying on a contradiction, the design of an optimal intellectual property regime, according to Robinson (1969), would be almost utopian. However, patents would be less relevant in industries whose competitive advantage lies in the 'know-how' (i.e., tacit knowledge).

competition—and the underlying operating costs reduction via technical progress—always leaves a pool of involuntary unemployed labour, causing a continuing divergence between productivity and real wages. On the other hand, reducing operating expenses is not costless since the technical change would systematically be capital-biased, thus entailing increased unit capital costs. So, even if the productivity-real wage ratio increased, the long-term rate of profit would show a downward trend. The first creative destruction deviation thus resembles the *reserve army* thesis of Marx (1867) and, to some extent, the *technological unemployment* predicted by Keynes (1932) for the mature stage of technical progress. Instead, the second deviation concerns the well-known Marxian secularly falling profit rate (Marx, 1867). Shaikh (1992, 2016) suggests that the growth dynamic tends to slow down as the profit rate decreases, giving rise to periods of stagnation and crisis.

Nonetheless, as Acemoglu and Robinson (2015) underline, the Marxian falling profit rate somewhat underestimates the endogenous power of technology. As an input independent of human and physical capital, knowledge can reduce labour and capital costs (if it reduces both in the same proportion, we have a Hicks-neutral technical shock). However, as mentioned, the long-run rate of profit can certainly decline not so much because technological change becomes excessively capital-biased but because the return on knowledge diminishes. That is, due to exhaustion of inventiveness or knowledge commons' privatisation (through underfunding of R&D and excessive patenting). In this context, it is likely that the lower the expected return on innovation, the higher the opportunity cost of continuing to innovate and, therefore, the greater the incentive to protect dominant positions through anti-competitive practices.

2.1.3 Schumpeterian and non-Schumpeterian market selection

Given the sunk-cost nature of innovation and entrepreneurship, knowledge non-rivalry, and structural uncertainty, no rational firm would undertake efficiency improvements without the prospect of gaining market power (Dosi & Nelson, 2010; Romer, 1990). However, to gain market power or grow, companies can either create or destroy wealth (Mazzucato, 2013a). This fact further suggests that *the market efficiency benchmark should be creative destruction rather than perfect competition*.

When market power and industrial shares result from innovations that create new goods or services, differentiate existing ones, or reduce costs, the above-average profits would only mirror economy-wide contributions. Thus, social wealth is expected to improve through sustained growth and productivity-based income distribution. Here, creative destruction is expected to operate fully as long as competitive pressure persists, with optimal flows of knowledge and financial resources that safeguard proper appropriateness and inhibit any entry or growth barrier. However, if business activities are oriented towards generating profits without creating value, inequality and growth are likely to be affected simultaneously (Stiglitz, 2016). In particular, if firms are enabled to increase their earnings or market share via pre-emptive mergers or acquisitions, limit-price strategies, collusion, price discrimination, or lobbying regulatory institutions, for example, a transfer (or extraction) of wealth is likely to occur while innovation is discouraged. In addition, if investment opportunities rely on liquidity or accumulated capital and not on the idea's quality or the project productivity, potential competition is expected to be undermined, which may reinforce market power not sustained by innovative activities.

Therefore, the "competition for the market" may be characterized by the "turbulent" coexistence of what Covarrubias et al. (2020) have designated as 'good concentration' and 'bad concentration,' what Aghion et al. (2022b) have denoted as 'good rents' and 'bad rents,' what Mazzucato (2013a) has characterised as 'Ricardian rents' and 'Schumpeterian profits,' or, what can be called as 'Schumpeterian and non-Schumpeterian rents.' To harmonise the different approaches, this thesis embraces the definition of (non-Schumpeterian) rents proposed by Lazonick and Mazzucato (2013), namely: (non-Schumpeterian) rents mean any income obtained in excess of the reward corresponding to the contribution of a production factor to the value creation. As far as the industrial dynamics are concerned, any firm entry, expansion or survival not strictly derived from inter-firm differentials in innovation and productive investment is considered a *non-Schumpeterian market selection.*

2.2 Empirical regularities on firm dynamics, job creation, and productivity growth

2.2.1 Evidence on Schumpeterian competition, entry, and dominant firms

The literature shows that productivity differences explain an important part of business entry, growth, and failure (see Syverson, 2011, for a survey). In the US manufacturing sector, in particular, the reallocation of inputs and outputs has been productivity-enhancing, accounting for up to 50% of aggregate efficiency growth during the 90s (Foster et al., 2001). Furthermore, previous studies suggest that industries with a higher elasticity of substitution among producers increase the market's minimum productivity threshold, reduce technological dispersion, and thus increase the industry's average productivity. In particular, Syverson (2004) found that low-productivity firms find it more challenging to survive in highly clustered markets. Consumers can more readily switch from one supplier to another when firms are highly agglomerated in one market. In particular, a shorter geographical distance among competitors reduces search and transportation costs, thus facilitating substitution among quality- or cost-asymmetric producers. In this case, easier product substitutability makes market structure and firm dynamics more dependent on relative efficiency and innovation.

Aghion et al. (2015, 2018) found that, in 'neck-and-neck' markets (i.e., with a lower gap between leaders and followers), the lower the industrial Lerner index (i.e., the price-cost margin), the larger the incentive to escape competition and, therefore, the larger the within-firm productivity growth. On the contrary, increased competition appears to reduce the innovation of laggards, especially if the time horizon is short (Aghion et al., 2018), while Mazzucato and Parris (2015) uncovered that R&D-intensive companies grow even faster when the competitive regime is fierce, that is, with less concentration and higher market share instability.

Entrepreneurs should play a critical role in introducing technological improvements that some rent-seeking incumbents do not volunteer. At the same time, the resulting competitive pressure also induces others to undertake productive responses to preserve their market position. This process is expected to nurture technological change, allow prices to get right, and prevent the entrenchment of monopolies (Robinson, 1969; Schumpeter, 1942). In this regard, Carreira and Teixeira (2011a) show that new companies enhance aggregate productivity growth by replacing less productive units and compelling established companies to improve their performance via increased competition.

However, increasing evidence shows that the median entrant is less productive than its (median) incumbent counterpart, while its survival probability is very low, with a large fraction of firms exiting the market during the first five years (Caves, 1998; Decker et al., 2014). Though start-up firms generate numerous jobs, they also destroy many others, so their net impact on job creation is somewhat limited. According to Nightingale and Coad (2014), they cause more churning than economic growth. The empirical record suggests market segmentation may be a likely outcome, where infant firms mainly displace their less productive young counterparts (Decker et al., 2014; Geroski, 1995). This process, in principle, generates (small) efficiency gains; however, the main point is that entry itself does not turn out to be a catalyst for creative destruction.

The greatest contribution of entrepreneurship appears to come from the distribution's right tail. A stylised empirical fact shows that the firm's growth rate distribution is highly right-skewed, especially for young firms (Coad et al., 2014; Decker et al., 2014). Although most newly born companies fail after entry, those that survive to exhibit much higher growth rates than mature ones. High-growth young firms then generate the largest contributions to net job creation. Moreover, the evidence shows that these high-growth young companies are more productive and innovative (Czarnitzki & Delanote, 2013). Therefore, their higher efficiency and rapid growth also improve the industry's productivity.

What makes a start-up become a high-growth firm? According to Santarelli and Vivarelli (2007), their motivations are the first factor to be observed. Entrepreneurs guided by proper incentives (namely, demand, expected profitability, and technological opportunities) enjoy a much greater chance of survival and more vigorous post-entry growth. Instead, those who set up an enterprise to escape unemployment or be independent have little likelihood of success in a Schumpeterian game.

Human capital, in particular, seems to condition entrepreneurship prosperity to a large extent. Santarelli and Vivarelli (2007) indicate that founders' educational level plays a critical role in the survival probability and the post-entry performance of start-ups, especially if it is industry-specific. Moreover, Kato et al.'s (2015) findings suggest that greater entrepreneurial human capital (prior innovation experience and educational background) is more likely to yield innovation outcomes. Goedhuys and Sleuwaegen (2016) and Goswami et al. (2019) also show that higher human capital increases the chances that a company becomes a high-growth one, while Lehmann et al. (2019) suggest that educational provision settings were crucial factors in explaining the emergence of high-growth start-ups in Silicon Valley and Europe.

Since not only transformative entrepreneurship (or gazelles) but also subsistence (Decker et al., 2014), "muppets" (Nightingale & Coad, 2014), or "revolving-door" (Santarelli & Vivarelli, 2007) firms enter the markets,[23] it seems reasonable to argue that the best policy is non-intervention so that the market alone eliminates inefficient entrants. At most, the

[23] Underperforming infant firms (the counterparts of young gazelles) have been given various denominations in the literature. Decker et al. (2014) used the definition of 'subsistence entrepreneurship', while Nightingale and Coad (2014) called them 'muppets' and Santarelli and Vivarelli (2007) 'revolving-door' companies.

government should equalise ex-ante opportunities by strengthening human capital. Otherwise, policymakers are likely to foster the survival of 'zombie' firms (Caballero et al., 2008).

Nevertheless, the evidence suggests that non-competitive mechanisms also operate in markets, which become more critical as industries reach maturity and concentration rates are higher. Geroski (1995) and Bellone et al. (2008) have observed that industries are characterised not so much by entry barriers but by survival and growth barriers. Factors such as advertising intensity, technology intensity, and minimum efficient scale appear to be particularly stringent for start-ups, especially in mature industries (Geroski, 1995). Moreover, Bellone et al. (2008) show that the selection effect tied to industry characteristics, in terms of concentration and turbulence, mostly affects young firms. Hence, industry structures favour the survival of mature firms.

Highly digitised and computerised processes, which characterise modern industries, are likely to intensify entry and post-entry barriers, while managing Big Data imposes new barriers or fixed costs that very few infant companies can circumvent or afford (Grullon et al., 2019; Stiglitz, 2019). Moreover, network effects and ill-designed patent regimes also penalise entry and weaken the development of survivors (Grullon et al., 2019; Stiglitz & Greenwald, 2015). For instance, Heger and Zaby (2018) found a negative correlation between patent breadth and the threat of market entry,[24] while Cockburn and MacGarvie (2011) report that a 10% increase in patents lowers the entry rate between 3% and 8%.

Incumbent firms are, of course, aware of entrepreneurial heterogeneity. Thus, deterrence mechanisms are expected to operate selectively on those who survive (Geroski, 1995). Ultimately, when deterrence doesn't work, pre-emptive mergers and acquisitions can take action to avoid potential competition, facilitated by the high incentive that young innovative entrepreneurs have to sell their company at an attractive price (Stiglitz & Greenwald, 2015). Nevertheless, these mergers and acquisitions (M&A) are less productivity-enhancing than common wisdom assumes. There is little evidence of increased efficiency after the merger, while the post-merger incentive to innovate generally weakens (Blonigen & Pierce, 2016; Haucap et al., 2018). As a result, M&A appear to strengthen the dominant firms' market power.

[24] That is, a wider breadth of patents is effective in protecting the product market against market entry of competitors, serving as entry barrier.

Credit rationing particularly affects young and small enterprises (Aghion et al., 2007; Carreira & Silva, 2010). Its importance increases in highly innovative markets as risk is higher and ideas are non-contractible. Without an adequate provision of risk capital, entry and growth are unlikely to be determined by the project's efficiency but rather by its collateral capacity. The evidence shows that financially constrained, *though productive*, firms face a higher failure risk and grow slower (Carreira et al., 2021; Musso & Schiavo, 2008). Bottazzi et al. (2014) and Lee (2014) also found that financial constraints prevent fast-growing young companies from seizing attractive growth opportunities. In the same vein, Schneider and Veugelers (2010) indicate that access to finance is the most important factor hindering the knowledge activities of innovative firms, especially if they are young. So, in the long run, increasing risk, concentration, and the rising cost of technology are likely to impair finance availability, weakening the entry and growth of the 'liveliest would-be innovators' (Robinson, 1962; Stiglitz & Greenwald, 2015).

On the whole, these findings suggest that deep-pocket mature firms enjoy a strategic advantage in product market competition. Fresard's (2010) findings, in particular, indicate that higher cash reserves lead to more remarkable market share growth at the expense of rivals. This cash effect is most significant when competitors face stringent funding constraints and when the number of strategic interactions among contenders is substantial. The author also argues that the cash stocks of established firms significantly curb potential competitors' entry while distorting the investment decisions of their rivals. Finally, this advantage is countercyclical since financially stronger companies can, and have greater incentives to, lower their prices to prey on weaker competitors during recessions (Braun & Raddatz, 2016).

Therefore, large mature enterprises seem to have an important entrenchment ability, thus undermining one of the creative destruction fundamentals: the limited temporality of dominant positions. As Geroski et al. (1985) suggest, their advantage chiefly lies in what accumulation allows them to make, both to invest or innovate and to elude selection forces (sometimes successfully and sometimes not). In this respect, Geroski and Toker (1996) observed that the turnover of market leaders in the UK was relatively low from 1979 to 1986. This relationship is far from suggesting any notion of perfect mobility, as companies in the top 5 in 1979 were likely to remain in that group for around 18 years. In a more recent study, Kato and Honjo (2009) found that market leaders maintain their leading positions for 20 years in Japanese manufacturing industries (on average). Furthermore, their findings indicate that market leadership tends to persist in capital-intensive and cartelised industries. In contrast, it is less likely to continue in volatile demand, R&D-intensive and import-intensive industries.

Kato and Honjo (2006) also found that the market shares of leading firms tend to remain more stable in highly concentrated markets, whereas Mazzucato (2000) observed that the larger the market share instability, the more intense the creative destruction. Indeed, the instability of market shares would have been very high during periods of radical innovation, whereas decreased turbulence reflects greater collusion. Moreover, there is evidence that market power inhibits response to a given level of post-innovation returns and that indirect effects on innovation capacity are relatively small (Geroski, 1990). In other words, a higher concentration weakens industrial dynamics and favours a quiet life for dominant firms while undermining the adoption and generation of new technologies.

2.2.2 Exit barriers and their influence on productivity growth

The bulk of the empirical record shows that low efficiency is one of the main determinants of business exit (Bottazzi et al., 2011; Carreira & Teixeira, 2011b). Furthermore, this destruction process does not occur suddenly. Instead, closing firms exhibit a decreasing productivity profile over several years before their bankruptcy (Carreira & Teixeira, 2011b).

Transportation, switching and search costs may allow a low-productivity firm to survive in the short term. However, in the medium and long term, high-cost or low-quality firms experience a reduction in their profits due to a decrease in the unit profit margin (forced to match market prices) and a loss in sales. This impaired profitability prevents these firms from offering a wage premium to hire highly skilled workers.[25] It also weakens its investment capacity due to more significant difficulties in translating retained earnings into new assets and larger restrictions in accessing external financing. Both factors contribute to a further deterioration of efficiency and, therefore, competitiveness. Unless an inefficient firm successfully carries out restructuring strategies, its bankruptcy is imminent.

Business bankruptcy is therefore expected to improve aggregate technological efficiency since resources are reallocated to more productive uses. At the same time, market decongestion increases the expected rate of return on any investment, thus encouraging the

[25] Growing evidence shows that, after controlling for observable and unobservable employee characteristics, employers offer different wages for potentially identical workers and that this wage dispersion is highly correlated with the distribution of firm productivity (Card et al., 2018; Mortensen, 2010).

entry of new and better projects. As a result, one should expect a high correlation between entry and exit rates. The evidence seems to confirm this presumption (Carreira & Teixeira, 2016; Caves, 1998).

The empirical literature has nevertheless identified that financial constraints and exit barriers can mitigate or even reverse the efficiency of corporate bankruptcy, especially during periods of credit crunching (Carreira & Teixeira, 2016). While the former causes the failure of more productive firms but with less liquidity and collateral capacity (Miller & Stiglitz, 2010), the latter prevents the exit of unviable (zombie) enterprises (Caballero et al., 2008).

Concerning exit barriers, an increasing body of literature has observed that a substantial proportion of firms with low productivity and profitability have managed to survive for a prolonged interval (Acharya et al., 2019; Carreira et al., 2022). The survival of poorly performing firms suggests the presence of creditor forbearance, high sunk costs of exit, ill-designed insolvency regimes or inefficient government subsidies. Still, we can expect persistently low returns and little innovation in industries with high exit barriers (Geroski et al., 1985).

Caballero et al. (2008) theoretically demonstrated that when the exit margin is hindered by allowing the survival of firms that otherwise would exit the market, the adjustment to adverse shocks is likely to be made through more productive units. The resulting congestion reduces profitability margins, thus increasing the minimum productivity threshold for healthy projects. A higher minimum productivity threshold discourages investment by both new and incumbent firms while increasing the destruction of relatively more productive units. Therefore, aggregate productivity is harmed not only by the preservation of 'zombie' firms but also by the negative externalities they generate on the entry, growth, and exit of non-zombie projects.[26] Furthermore, since zombies face a lower productivity threshold than non-zombies, the productivity gap between zombies and non-zombies widens with the share of zombie firms, which entails increased technological dispersion within industries.

Empirical evidence has confirmed that the higher the zombie share in an industry, the lower its aggregate productivity, while the growth and investment of healthy companies appear to decline as zombie retention increases (Caballero et al., 2008; McGowan et al., 2017c).

[26] The "sclerosis" and "scrambling" effects, respectively (Caballero et al., 2008).

Moreover, higher exit barriers are also associated with a weakened reallocation of capital and labour (Gouveia & Osterhold, 2018; McGowan et al., 2017b).[27]

The issue is why the zombies' creditors continue to support them *for an extended period* rather than enforce their debt claims. Though debtors have privileged information on their financial and real indicators, these asymmetries are expected to diminish as time goes by. So, provided profitability mirrors productivity, the former variable is expected to signal efficiency in credit-rationed markets (Coad, 2010). Thus, one might presume creditors would try to speed up exit selection (blocking new loans and enforcing debt claims) when faced with zombie borrowers. However, the literature suggests that creditors' response may depend on the debt's nature, the degree of asymmetric information, the risk associated with liquidation, and institutional designs.

Peek and Rosengren (2005) observed that banks granted loans under criteria other than efficiency and profitability in Japan during the 1990s. The authors found that the lower the profitability, the greater the likelihood of new bank financing. Also, banks with reported risk-based capital ratios close to those required were more likely to increase loans to firms. And the perverse relationship between underperformance and increased likelihood of borrowing was stronger in more undercapitalised banks. Consequently, banks may be incentivised to continue lending to underperforming companies to avoid further increasing their reported non-performing loans, allowing these otherwise bankrupt firms to keep afloat.[28]

Nevertheless, Jaskowski (2015) argues that banks engage in zombie lending not only to overstate their capital but also to prevent further losses from fire sales.[29] So, it implies that the larger (and the more specific) the assets at stake, the greater the creditors' incentive to prevent their zombie borrowers from going bankrupt, particularly during crises (Hansen & Ziebarth, 2017). This effect is likely to worsen when the debt is more dispersed, and the

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[27] Several studies point to the prevalence of zombies as one of the main causes of Japan's economic stagnation during the 1990s. For example, Kwon et al. (2015) estimate that Japanese annual productivity growth would increase by one percentage point during that decade without zombie lending. The hypotheses of Caballero et al. (2008) have also been tested in other countries with very similar results. For instance, Lam et al. (2017) for the Chinese economy from 1998 to 2013; McGowan et al. (2017c) for nine OECD countries during 2003-2013; Andrews and Petroulakis (2017), for eleven European countries during the 2001-2014 interval; and Gouveia and Osterhold (2018), for Portugal in the 2006-2015 period.

[28] Andrews and Petroulakis (2017) extended the research to OECD countries and found that zombies are indeed connected to weak banks.

[29] Diamond and Rajan (2011) suggest that impaired banks may prefer to retain their illiquid assets rather than sell them, simply because they see the marginal cost of additional illiquidity as small.

business' piecemeal sale further depresses asset values, as in large firms (Franken, 2004).[30] Hence, despite reducing information asymmetries or increasing supervision, banks may still be incentivised to avoid the exit of unviable firms, especially in the case of large borrowers.[31]

2.2.2.1 Insolvency framework and zombie firms

Efficient insolvency and restructuring framework can play a fundamental role in reducing distortions in the market selection and resource reallocation caused by zombie survival, especially if it promotes the recovery of weak (but viable) firms with temporary financial distress and the exit of non-viable ones (McGowan et al., 2017b, 2017a). The ability to differentiate viable from non-viable companies in insolvency events is, however, affected by asymmetric information in the capital market and by the different incentives that managers, shareholders, and creditors have in the ex-ante and ex-post stages of those events (Aghion, 1992; McGowan & Andrews, 2018).

Therefore, solving financial conflict depends critically on ownership and debt structures. For instance, a typical Small and Medium-sized Enterprise (SME) has few owners with almost no division between managers and shareholders. Moreover, its debt mainly depends on banks, which collateralise their financing against assets (Bergthaler et al., 2015; Franks & Sussman, 2005). In contrast, large companies are characterised by complex ownership structures, greater debt dispersion, and lower bank dependence. Similarly, the complexity of ownership and debt structures is likely to delay the resolution of insolvency conflict, thus depressing the firm value (Franken, 2004). Therefore, the debate on insolvency legislation design has focused on which orientation generates more efficient results. In other words, is a creditor-oriented regime better than a debtor-oriented regime or the other way around?

Creditor-oriented regimes promote agile liquidations and an immediate recovery of secured debt, accompanied by a quick dismissal of managers. These regimes also preserve legal certainty, so the applicable redistributive regulation is the absolute priority rule, thus emphasising the protection of the creditors' negotiated ex-ante rights (Aghion, 1992; Cirmizi et al., 2012; McGowan & Andrews, 2018). The maximisation of ex-ante and ex-post

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[30] Note that one might argue that exit barriers would be reduced if the insolvency law increased creditor protection so that quick liquidations mitigate asset depreciation, thereby reducing incentives for zombie lending. However, the evidence shows that regimes that overprotect creditors cause excessive liquidation of viable firms, delays in bankruptcy filings and a reduction in credit demand that discourages investment and innovation (Acharya & Subramanian, 2009). We address this in more detail in the following subsection.

[31] However, it is essential to analyse whether the gains in aggregate demand and employment compensate for the efficiency losses that "too big to fail" incentives entail, especially in economic crisis.

efficiency is sought through a lower general interest rate and the mitigation of overinvestment after and insolvency, respectively. Nevertheless, a creditor-oriented design can incentivise debtors to delay bankruptcy, while it may also result in excessive liquidation of viable firms (Adler et al., 2013).

Alternatively, a debtor-oriented regime allows a reorganisation agreement that (i) leaves the manager in office during the such 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, but in case of dissent, the plan can be imposed by a majority ("cram-down") (Aghion, 1992; McGowan & Andrews, 2018). Hence, timely insolvency statements and greater recovery probability of viable firms are expected, increasing ex-ante and ex-post efficiency. Yet, since creditors are less protected, investment risk may increase (Rodano et al., 2016). Moreover, as unsecured creditors and managers/shareholders can seek business reorganisation at all costs, the recovery likelihood of unviable firms may also be greater (Franken, 2004).

Overall, the losses obtained from insolvency regimes that overprotect creditors appear to exceed their gains. The threat of premature liquidation would also reduce credit demand, and companies tend to preserve higher levels of liquidity (Vig, 2013). This reduction in optimal leverage is likely to adversely affect investment and innovation, especially in knowledge-intensive industries (Acharya & Subramanian, 2009).

Finally, the evidence suggests that when it is possible to negotiate a reorganisation agreement, its success is inversely proportional to the number of creditors classes involved (Brunassi & Saito, 2018; Kalay et al., 2007). Furthermore, the larger and older the company, the more likely it is to remain a going concern after the insolvency statement (García-Posada & Vegas Sánchez, 2018). Also, the higher the share of secured debt, the lower the probability of reorganisation agreements' approval, even if the liquidation is inefficient, and conversely for unsecured debt (Brunassi & Saito, 2018; Ivashina et al., 2016).

International best practices recommend that a balance between creditors' and debtors' rights increases the ex-ante and ex-post efficiency of insolvencies (Cirmizi et al., 2012; Djankov et al., 2008). Accordingly, McGowan and Andrews (2018) suggest 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 the declaration of insolvency, 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 with the priority given to 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.

Carreira et al. (2022) found that, on average, a zombie firm requires three years and six months to exit and three years and two months to recover. In such a context, the design of bankruptcy regimes is especially relevant to reducing those barriers that delay the transition of zombies to where competitive pressure should naturally lead. Nonetheless, Carreira et al. (2022) and Fukuda and Nakamura (2011) also revealed that zombies are not inherently unviable firms, as recovery is a possible route. On the contrary, many are financially distressed, and a poorly designed regimen can trigger *myopic* selection, driving potentially viable (small) companies out of the market. The results of Fukuda and Nakamura (2011) and Carreira et al. (2022) suggest that strategies such as downsizing, technological restructuring, and debt restructuring effectively increase the recovery likelihood of zombies.

Therefore, efficient insolvency regimes can strengthen market selection through greater responsiveness at the exit margin and increased competition impelled by recovering zombies, also reducing aggregate losses linked to job destruction. Moreover, McGowan et al. (2017b) found that insolvency regimes that hinder firm restructuring, more than impairing the recovery of relatively more productive zombies, increase the chances of a healthy company becoming a zombie. Hostile regulations for restructuring can also increase the percentage of capital sunk in zombies (McGowan et al., 2017b) and hinder the technological catching-up of laggard firms (McGowan et al., 2017a).[32]

[32] The impact on capital reallocation and technological diffusion is expected to be greater in dynamic industries and more dependent on external financing.

3 The productivity slowdown of the new century

3.1 Long-term evidence on business dynamism and market concentration

Growing evidence shows that business dynamism and resource reallocation have weakened in most developed economies over the past few decades and before the pandemic crisis (Calvino et al., 2020; Decker et al., 2016; Haltiwanger et al., 2014). This phenomenon has been concomitant with a widespread increase in market concentration (Affeldt et al., 2021; Bajgar et al., 2019; De Loecker et al., 2020) and within-industry productivity dispersion (Andrews et al., 2015; Decker et al., 2018), and with a secular decline in the labour share (Autor et al., 2017; Karabarbounis & Neiman, 2014). Moreover, all this has been happening along with a well-known *productivity slowdown*.

For the US economy, Decker et al. (2016) and Alon et al. (2018) reported that the entrepreneurship rate had declined steadily since the 1980s, accompanied by a lower share of young firms in aggregate employment. Decker et al. (2016) also observed that the employment growth rate distribution has structurally changed from the beginning of the new century as its skewness and dispersion have been markedly reduced. This decreased skewness seems to be driven by a lower propensity of young firms to become high-growth units, even in the high-tech sector. As a result, the industrial average age is now higher (Alon et al., 2018). According to Alon et al. (2018), the start-up deficit and the industry's ageing have led to an annual drop of 0.1 percentage points (p.p.) in the US productivity growth rate during 1980-2014 (identical to a cumulative effect of 3.1 p.p.).

Moreover, the US job reallocation rate has fallen by about 10 p.p. between 1979 and 2011 (Hathaway & Litan, 2014). Thus, declined entrepreneurship, slower post-entry growth, and decreased reallocation entail a weakened selection effect on technological efficiency growth, as shown by Decker et al. (2017). Furthermore, downward competitive pressure is expected to discourage productive investments by incumbents, which also impairs efficiency growth by reducing the 'within' component. Again, Decker et al. (2017) seem to support this presumption.

On the other hand, several studies reveal that concentration and market power in the US industries has significantly increased over the last two decades (Autor et al., 2017;

Covarrubias et al., 2020; Eggertsson et al., 2021; Grullon et al., 2019). For instance, Grullon et al. (2019) found that the median increase in the Herfindahl–Hirschman Index (HHI) in a typical three-digit industry was 41% between 1997 and 2014, while the corresponding average increase was 90%. De Loecker et al. (2020), using the ratio of sales to costs-of-goods-sold to estimate markups, also found that average markups began to increase in 1980 from 21% to 61% in 2016. Yet, this increase mainly occurred in the distribution's upper percentiles, whereas the median has not changed.[33] In addition, De Loecker et al. (2020) show that high-markup firms have reduced their investment, especially in intangible assets, reinforcing the idea that producers have fewer incentives to innovate without current and potential competition.[34] Covarrubias et al. (2020) corroborate these results. Finally, De Loecker et al. (2020) and Autor et al. (2017) show a negative correlation between market power (sales concentration) and labour share. Thus, a higher degree of monopoly seems to induce income redistribution between capital and labour, as Kalecki (1954) early suggested.

Meanwhile, Gutierrez and Philippon (2019a, 2020) have cast doubt on the ever-beneficial role of dominant firms. Covarrubias et al. (2020) show that the replacement likelihood of a Top 4 industry leader was 35% during the 1980s, increased to 40% in the mid-1990s, and is only 25% nowadays. Moreover, Gutierrez and Philippon (2019a, 2020) found that dominant firms' relative productivity has not increased, and their contribution to aggregate productivity growth has decreased by about 40% during the higher concentration and lower leadership turnover interval (i.e. since 2000). Gutierrez and Philippon (2019a) further show that today's *superstar firms* contribute less to the economy than their 1990s counterparts. Lastly, Autor et al. (2017) and Grullon et al. (2019) identified a positive correlation between patent and market concentrations. Accordingly, obstacles to diffusion flow have likely facilitated a greater sales conglomeration in the distribution's upper tail. Therefore, the evidence suggests that US industrial leaders have somehow been protected against competitive forces over the past twenty years, reducing innovation and business dynamism.

The long-run US evidence of business dynamism and market concentration is abundant. Uncovering those relationships in the country that experienced one of the deepest liberalisation processes over the past four decades is not trivial. However, since long-term evidence in other developed countries is very scarce, our ability to understand the character

[33] De Loecker et al. (2020) further report a stronger market share reallocation from low- to high-markup firms.

[34] Gutierrez et al. (2021) argue that higher entry costs explain the increase in market power. Rising entry costs also reduce aggregate demand and investment, so low inflation and higher market power can coexist.

of the underlying forces is somewhat limited. The 1980s coincided with the global rise of neoliberalism *and* the emergence of the new technological paradigm linked to the ICT revolution.

Concerning firm dynamics, Calvino et al. (2020) observed similar decreasing trends in business dynamism, resource reallocation, and young firms' activity in the rest of the OECD countries. Although there would be a connexion between the heterogeneity of institutional settings and the nature of the business dynamism slowdown, these secular trends transcend specific national contexts. Nevertheless, their analysis only covers the period 2000-2015. To our knowledge, the only equivalent inquiry applied outside the US is that conducted by Bijnens and Konings (2020), who analysed the Belgian business dynamics from 1985 to 2014. The authors also found a long-term decline in entrepreneurship and reallocation rates and reduced dispersion and skewness of the employment-weighted growth rate distribution. According to Bijnens and Konings' findings (2020), the decline in Belgian business dynamism has led to a change in the composition of the business landscape toward older, slower, and less volatile firms.

Regarding market power and industrial concentration, De Loecker and Eeckhout (2018) found that markups (i.e., price over marginal cost) increased from about 1 to 1.6 in Europe and from 1 to 1.5 in Asia between 1980 and 2016. Furthermore, Affeld et al. (2021) observed that the HHI increased from 0.25 to about 0.30 between 1995 and 2014 in the typical EU *antitrust market*.[35] Outside of these exceptions, studies in other advanced economies cover only the new century. For instance, according to Bajgar et al. (2019), concentration increased in 74% of European industries from 2000 to 2014, with a rise of about five percentage points in the eight-firm concentration ratio (C8) in the average European sector.[36] Similarly, Bighelli et al. (2021) observed an increase in the European HHI of about 43% between 2009 and 2016. In any case, the evidence confirms that Europe has not been immune to increased market concentration.

[35] One of the main advantages of this study is relying on 'antitrust market' definitions (established by the European Commission for merger control) of markets affected by mergers during the analysed interval. Hence, the study provides more precise measures of the markets' boundaries regarding geography and the elasticity of substitution.

[36] The countries for Europe include Belgium, Germany, Denmark, Estonia, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Slovenia, and Sweden.

3.2 Competing hypotheses on the decline of industrial dynamics and technical progress

Weakening business dynamism (with higher mobility barriers), more concentrated markets with veteran and entrenched leaders, and slowing technological change suggest that creative destruction is running out of steam. Analysing and connecting the different *long-term trends* in industrial dynamics, job creation, distribution, and productivity is crucial since the phenomena are interdependent and the competitive regime is not static.

Economists from different theoretical approaches try to explain this phenomenon of concentration and stagnation. However, we are far from reaching a consensus. In this regard, Covarrubias et al.'s (2020) work is a crucial starting point to contrast the extant literature's competing hypotheses. The authors argue that theories seeking to explain the new-century industrial dynamics can be based on two types of concentration: "good concentration" and "bad concentration" (i.e., Schumpeterian and Non-Schumpeterian concentration). In the same vein, albeit somewhat related, we should add the "lower responsiveness" hypothesis of Decker et al. (2018) and the zombie firms' theory of Caballero et al. (2008), both reflecting a non-Schumpeterian market selection.

The "good concentration" group comprises two non-mutually exclusive theories. The first hypothesis, due to Autor et al. (2017), proposes that enhanced information flow led by ICT usage enabled consumers to become more sensitive to price and quality differentials, thus favouring concentration towards highly productive firms. In line with Aghion et al. (2001) endogenous growth model, presented in Chapter 2, less incomplete information leads to increased elasticity of substitution among producers, which, in Bertrand's scheme with asymmetric costs, causes *the winner takes all* outcome. Furthermore, Autor et al. (2017) found a positive industry-level relationship between TFP growth and market concentration in a pooled sample for 1982-2012. However, it is worth noting that Autor et al. (2017) did not rule out that, after winning the Schumpeterian competition, *Superstar* firms may have raised entry barriers to protect their competitive advantages.

The second hypothesis emphasises the role of intangible capital and the resulting increasing returns to scale. Aghion et al. (2022a) suggest that intangible assets gave leading companies a process efficiency advantage challenging to imitate, so the technological gap becomes very persistent. Moreover, according to Aghion et al. (2022b), knowledge anchored in efficiency advantages spills over hardly (or very slowly), allowing lower unit cost firms to enjoy high and persistent markups. Aghion et al. (2022a) then claim that a more significant efficiency advantage encourages leading firms to expand into broader product lines, increasing productivity but discouraging new innovators over time (due to lower expected profit margins).

In contrast, “bad concentration” theories rest primarily on barriers to competition. Akcigit and Ates (2019), for instance, argue that a slow spread of knowledge explains the observed decreasing dynamism. This decline in knowledge diffusion—due to more intensive protection of intellectual property—negatively affects current and potential competition, favouring concentrated sectors’ prevalence. Moreover, Gutierrez and Philippon (2019b) suggest that lax antitrust enforcement (leading to an excessive incidence of M&A) and lobbying by dominant firms triggered an increase in entry costs.

Economists from other theoretical approaches further suggest that declining business dynamism, increasing market concentration and productivity slowdown are rooted in the prevailing institutional framework that has particularly favoured large corporations (Lambert, 2019; Mazzucato et al., 2020; Reich, 2015; Stiglitz, 2019; Taylor & Ömer, 2020; Tepper & Hearn, 2018).

For example, Stiglitz (2019) claims that, in the absence of *appropriate* public intervention, monopoly, once achieved, is easy to maintain, and, from that position, “rent-seeking” behaviour is likely to prevail. Based on a simple flow perspective, Stiglitz (2016) proposes that $I = sY - (1 - s)\Delta R$, where I denotes investment, s saving share, Y national production, and R rents. Consequently, an increase in R lowers I, all else constant. In other words, obtaining profits from rentier activities becomes a powerful disincentive to investment. As a result, large companies are specialised in developing “innovations” to expand their dominant position without engaging in new productive investments (e.g., raising entry barriers or removing potential competitors). Moreover, the concentration of economic power inevitably results in political power, a facilitator of rent extraction (Stiglitz, 2019). As these (non-Schumpeterian) rents are not anchored to value creation, rent-seeking behaviour explains both growing inequality and productive stagnation.

Lambert (2019), focusing on macroeconomic reasons, contends that the slowdown in entrepreneurship is correlated with higher household debt levels. This indebtedness, in turn, has weakened access to funding by potential entrepreneurs, an environment that would place “deep-pocket” incumbents in a relatively favourable position.

It is important to note that *bad concentration* theories seem to resemble Joan Robinson's (1969) hypotheses on productive stagnation. As discussed in Chapter 2, Robinson (1969) argued that the systemic reproduction of the so-called *golden age of capitalism* (the simile of creative destruction) becomes unstable when inventiveness runs out, the knowledge flow is hindered, and the competitive mechanism is clogged. In turn, her view on weakening the competitive mechanism—in competition *à la Schumpeter*, in practice—has to do with the prevalence of persistent dominant firms. She pointed to economies of scale, financial constraints, advertising intensity, mergers and acquisitions, and limit-pricing strategies as the leading causes.[37]

From the firm dynamics literature, Decker et al. (2018) developed a theoretical model to disentangle whether the secularly weakened business dynamism in the US economy is due to a change in the dispersion of shocks that firms face or instead to a change in the response of firms to shocks (called the lower responsiveness hypothesis). In essence, a lower intensity of productivity shocks implies diminished possibilities for efficiency improvements mainly caused by a technological paradigm's exhaustion. In such a scenario, one would expect imitation and selection to prevail over innovation, thus triggering technological convergence and lower dynamism. Therefore, weakened responsiveness of business growth to productivity differences (i.e., depressed market selection) accompanied by decreased technical variance indicates an overall maturity of industries. In contrast, a lower degree of responsiveness accompanied by higher technological dispersion reflects reallocation frictions.

Finally, some authors suggest that declined business dynamism is also rooted in the exit margin. Several studies show that zombie firms have multiplied during the new century, particularly in the European case (McGowan et al., 2017c). The higher zombie incidence seems to have occurred in a context in which undercapitalised banks had greater incentives to continue lending to their troubled (zombie) borrowers to avoid (or delay) a further increase in their reported non-performing loans, particularly during the Great Recession (Andrews & Petroulakis, 2017). In addition, inefficient insolvency regimes appear to have exacerbated this phenomenon (Carreira et al., 2021; McGowan et al., 2017b). Hence, while facilitating the artificial subsistence of low-productivity enterprises, the increase in exit barriers is expected to have impaired the entry, growth, and survival of more productive firms, thus

[37] That is, with what Geroski et al. (1985) later called structural and behavioural barriers to competition.

hampering aggregate productivity and job creation (Caballero et al., 2008). Moreover, since zombies face a lower productivity threshold than non-zombies, the productivity gap between zombies and non-zombies widens with the share of zombie firms, increasing technological dispersion.

Exit barriers, such as bank forbearance and inefficient insolvency regimes, are certainly barriers to reallocation that weaken responsiveness. Furthermore, as exit barriers affect entrepreneurship and investment by potential competitors, a leading firm embedded in a zombie environment is likely to preserve its dominant position with less effort.

3.3 Contrasting theories and main propositions

Each theory claims to explain the new-century trends of technological stagnation, market concentration and weakened business dynamism. For this reason, the contribution of Covarrubias et al. (2020) becomes highly relevant. Since patterns are systemically connected, the challenge is explaining the entire phenomenon and not just a few components.

In particular, Covarrubias et al. (2020) developed a competitive selection model intending to explain all the trends. Assuming a strategic game among firms with heterogeneous costs, we should first differentiate the number of companies that enter ($\widehat{N}$) and the number of those that actually produce (N). Companies that enter must pay a sunk entry cost κ only for the right to produce. However, after entry, all firms i draw productivity ω_i (from the same productivity distribution) and decide whether to produce with fixed operating cost ϕ_i and markup μ_i. Therefore, we have active producers for any $i \in [0, N]$, while all firms $i \in \left[N, \widehat{N}\right]$ exit prematurely. The consumption system is such that the individual demand curve facing each company is given by:

$$y_i = h_i Y \left(\frac{p_i}{P}\right)^{-\alpha}, \tag{3.1}$$

where Y denotes industry demand, P the industry price index, h_i the firm-level demand shocks, and α the elasticity of substitution among producers (as in the model by Aghion et al. (2001) discussed in chapter 2). The firm sets a price $p_i = 1 + \mu_i/\omega_i$, and only firms with $\omega_i \geq \omega^*$ are active producers $\left(N = \left(1 - F(\omega^*)\right)\widehat{N}\right)$. Assuming for now that $h_i = 1$, the equilibrium profit function for firm i is given by:

$$\pi_i(\omega_i, \omega^*, PY, N) = \frac{\mu_i}{1+\mu_i}\left(\frac{\omega_i}{\Omega^*}\right)^{\alpha}\frac{PY}{N} - \phi_i, \tag{3.2}$$

where Ω^* denotes the average productivity of the industry, which depends on ω_i, the productivity distribution, the number of active producers, and the cross-demand elasticity α. Given the productivity threshold ω^*, the number of active producers $N = \left(1 - F(\omega^*)\right)\widehat{N}$ decreases with α, thus obtaining the typical *selection effect*. In other words, the higher the demand-side competition (given by α), the greater the productivity cutoff ω^*, and the lower the number of active firms N. Lastly, since entry only occurs until the expected value of taking a productivity draw is zero, it follows that:

$$\frac{E[\pi|\omega>\omega^*]}{(r+\delta)}\left(1 - F(\omega^*)\right) = \kappa, \tag{3.3}$$

where r is the discount rate, and δ is the (exogenous) exit rate. Hence, an increase in the elasticity of substitution among producers α (e.g., due to lower information frictions) leads to a decrease in $\left(1 - F(\omega^*)\right)$, a higher rate of failed entry (premature deaths), and increased profits for the remaining firms (selection effect). In contrast, an increase in entry costs κ (due to more significant barriers to competition) leads to lower entry, lower exit, and higher profits.

To analyse the role of intangible capital and returns to scale, the authors extend the model by assuming that firms can, upon entry, choose between two types of technology: a low fixed cost and low productivity technique (Ω_L, ϕ_L) or a high fixed cost and high productivity one (Ω_H, ϕ_H). For simplicity, let us ignore the idiosyncratic differences within each type of technology, so the profit function is now:

$$\pi(\omega, \phi) = \frac{\mu}{1+\mu}\left(\frac{\omega}{\Omega}\right)^{\alpha-1}\frac{PY}{N} - \phi, \tag{3.4}$$

The choice of technology depends on the size of the market and the cross-demand elasticity α. Thus, firms have more incentives to switch to the Ω_H technology when demand-side competition is high (given by α). Suppose that firms decide to make the switch. In that case, the entry condition $(E[\pi]/(r+\delta) = \kappa)$ becomes:

$$N = \left(\frac{\mu}{1+\mu}\right)\frac{PY}{\phi_H + (r+\delta)\kappa}, \tag{3.5}$$

As a result, a higher degree of substitutability among producers leads to greater use of increasing returns to scale technologies, resulting in greater market concentration.

Finally, the authors obtain a relationship reflecting the dynamics of market shares from equation (3.1). Specifically, if the market share s_i of firm i in industry j is given by $s_{i,j} = p_i y_i / P_j Y_j$, then it follows that:

$$s_{i,j} = \frac{h_{i,j}}{N}\left(\frac{(1+\mu_j)\omega_{i,j}}{(1+\mu_{i,j})\Omega_j}\right)^{\alpha_j - 1}, \tag{3.6}$$

with the volatility of log-market shares is by:

$$\sum_{i=1}^{2} \log\left(s_{i,j}\right) = \sum_{i=1}^{2} \log\left(h_{i,j}\right) + \left(\alpha_j - 1\right)^2 \sum_{i=1}^{2} \log\left(a_{i,j}\right), \tag{3.7}$$

where $\sum_{i=1}^{2} \log\,(a_{i,j})$ is the volatility of idiosyncratic productivity shocks. As a result, the higher is α, the more volatile are the market shares. Likewise, from this equation, we can also derive that an increase in α leads to increased leadership turnover and decreased persistence of market shares.

In short, according to the model's predictions, a higher cross-elasticity of substitution α should lead to an increase in concentration, productivity, investment, market share instability, leadership turnover, and exit hazard. Similarly, if returns to scale and intangible capital deepening account for long-term patterns, we should observe an upsurge in concentration, profits, intangible capital investment, and productivity of surviving firms. However, supposing that barriers to competition (embedded in κ) explain the phenomenon, increases in concentration and profit margins should be accompanied by a decline in productivity growth, exit rates, market instability, leadership turnover and investment.

After performing an empirical exploration, Covarrubias et al. (2020) show that *good concentration* explains the US industrial dynamics in the late 20th century. In contrast, a growing *bad concentration* has characterised economic behaviour since 2000. In other words, barriers to competition have dominated US markets over the new century. Akcigit and Ates (2019) instead suggest that declined knowledge diffusion between leaders and followers drives the undermined capitalist dynamics. However, given that no economy can be called competitive without *proper* knowledge and technology dissemination, this theory confirms that 'bad concentration' hypotheses explain the US slowdown in productivity.

Finally, note that the lower responsiveness hypothesis of Decker et al. (2018) provides critical elements that complement the predictions of Covarrubias et al. (2020). In a scenario of slow technological change, industrial followers are expected to catch up more quickly. At the same time, market selection, and the resulting efficient reallocation, should also foster the narrowing of the technological gap. As a result, when productive dispersion widens, instead of shrinking, we may infer a higher incidence of barriers undermining technological convergence and allocative efficiency.

These theoretical predictions are somewhat intuitive. However, given the conflicting interests and the interdependence of events, these models have the advantage of explaining all the trends holistically, coherently, and systematically. Furthermore, as the system is not static, the inquiry must also consider the technological paradigm's evolution since the dynamics of creation, destruction and value extraction probably mirror the paradigm's dynamics. In fact, most studies on business dynamism and concentration show that the trajectories of the high- and low-tech sectors have not followed the same pattern, especially over the 1990s. This result, however, is not surprising. Even though the technological revolution affected the entire economy, the dynamics of markets born with the technological paradigm are not the same as that of markets that incorporate it by altering the productive trajectories in force until then.

Therefore, in line with Schumpeter (Schumpeter, 1939), Dosi and Nelson (2010), and Perez (2010), I argue that creative destruction has likely dominated, with more vigorous innovation and market selection, at the beginning of the ICT revolution—particularly in those emerging markets—, thus reflecting the destabilising force of rising technological paradigms. Nevertheless, in line with Robinson (1969), Stiglitz (2016), Philippon (2019), and Mazzucato (2018), I further propose that productivity stagnation is an increasing function of non-Schumpeterian market selection. In other words, a function of rising barriers to competition that allows industrial dynamics not to be determined by innovation differentials. Moreover, as the expected return to innovation declines (i.e., when the paradigm enters the phase of diminishing returns), (non-Schumpeterian) rent-seeeking incentives are likely to increase. The evolution of business dynamics, market structure and productivity growth in the Portuguese economy from 1986 to 2018 enables us to assess which force ultimately prevails.

4 The dataset, time-consistent industry classification, and critical variables

4.1 Building time-consistent industry codes

The primary data is *QP-Quadros de Pessoal* of Portugal. To complement the industrial information of firms, I also use *FUE-Ficheiro de Unidades Estatísticas* and *SCIE-Sistema de Contas Integradas das Empresas*. In turn, the calculation of total factor productivity and the identification of financially distressed firms are only possible through the SCIE data set.

QP provides longitudinal, employer-employee information on all private-sector firms that employ at least one worker. This data has been collected annually by the Ministry of Employment since 1985 and provides information at the enterprise and establishment levels on the business structure and employment. The participation of firms with registered employees is mandatory, providing a high degree of coverage and reliability. Moreover, each company and worker have a unique identification number, allowing tracking them longitudinally and generating business variables from the establishment and worker data. The employer reports all the information (i.e., firm-, establishment-, and worker-level) and relates to the situation observed in the reference month.

QP includes all types of companies according to their legal nature—including, among others, single proprietorship, general partnership, limited liability firms, and corporations—as well as non-profit and for-profit entities. Variables at the firm level include industry, location, number of employees, number of establishments, sales volume, legal nature, and ownership structure (i.e., domestic and foreign shares), inter alia. As of 2010, QP has two variables that report the total number of workers (full-time and part-time). The former reports the number of workers observed in the reference month (October), while the latter reports the number of workers observed on the last day of October. Before 2010 companies only reported the first variable, so this option is used for the entire period.

The FUE file, compiled annually by the National Statistical Office (INE by its acronym in Portuguese) during 1996-2004, was used for coordinating and harmonising information on the business population. FUE received panel information from the various operations of the INE's statistical collection and production units and integrated administrative records from external entities. We can obtain demographic information, legal form, economic activity (at all levels of disaggregation), and social capital distribution in this database. For its part, the

SCIE is a longitudinal dataset that reports the corporate balance sheet, whose responsibility for annual collection has also been in charge of INE. The data is built from a mandatory survey for all companies registered in Portugal and contains information from 2004 to 2018. This dataset reports the structure, industry (at the highest classification level), revenues, output, inputs, and other elements related to companies' economic, financial, and competitive nature.[38] Firms have the same identification number in QP, FUE, and SCIE, a key feature that allows all three datasets to be linked.

Over the selected sample interval, three industrial classification methodologies have been in place: Portuguese Classification of Economic Activities (CAE by its acronym in Portuguese) Revision (Rev.) 1 (1985-1994), CAE Rev. 2 (1995-2006), and CAE Rev. 3 (2004 onwards). These changes introduce limitations for conducting any long-term time-series analysis that requires the use of industrial affiliation. For example, companies may switch from one sector to another without any real change in the underlying economic activity. Therefore, I implemented a homogenisation process to construct time-consistent industry codes. The objective was to classify all firms under Rev. 2, at least at 2-digits of disaggregation. Given that QP has industry codes at a maximum of only 3-digits in 1985-2009 and 4-digits from 2010 onwards, I first merged this dataset with the FUE and SCIE, which have codes at the highest classification level (6-digits in Rev. 1 and 5-digits in Rev. 2 and 3). Moreover, given that all the companies in SCIE were classified only according to Rev. 3, after merging, the same firm from 2004 to 2006 had a code of Rev.2 and another of Rev.3, a key advantage for the homogenization process.

Following Fort and Klimek (2018) and Autor et al. (2017), I applied the following three-step procedure:

i. I used the INE public concordance tables for all cases where a code (at the highest available disaggregation level) has a unique 2-digit match in Rev. 2.
ii. In cases with multiple destinations, I used the longitudinal data structure to transfer industrial information from the period companies were classified under Rev. 2 to the other periods (before 1995 and after 2006) whenever firms have not changed their economic activity. To illustrate, in the case of multiple destinations of companies operating before and from 2007, I assigned the 2-digit code they had before that year, provided they remained in the same industry after that.

[38] Unlike QP, both FUE and SCIE do not contain single-proprietorship enterprises.

iii. I performed a modal mapping only in the remaining cases (5.32% of total observations), so that each industry Rev.1 and Rev.3 was assigned the 2-digit Rev.2 code that was more likely to map to in the probabilistic mapping, determined by the mode.

Once this harmonization was applied, preliminary filtering of the raw data was required. In particular, companies not belonging to the productive sector (e.g., foundations, associations, unions, social security institutions, inter al.) and unreasonable observations (e.g., negative employment) were eliminated. To estimate firm growth and job creation and destruction rates (crucial for Chapter 5), I generated observations for the years a company temporarily did not report to QP—which was interpreted as a temporary closure—and for the year following the last time it reported positive employment—interpreted as a definitive exit. Thus, a temporary closure is one in which a firm reports positive employment in "t-τ," employment equal to zero in "t" and positive employment in "t+τ" (occurring the reopening in "t+1"). Likewise, a definitive closure occurs when the company reports positive employment in "t-τ," employment equal to zero in "t", and the identifier definitively disappears in "t+τ."

I pay special attention to intersectoral assessments according to the knowledge intensity level to map the different trajectories resulting from the emergence of the technological paradigm. To this end, I use the methodology developed by the Statistical Office of the European Union (Eurostat). The list of industries classified as knowledge-intensive is found in Table 4.1 (two digits).

Table 4.2 shows the evolution of the employment composition in each Portuguese sector during 1985-1990, 1991-2000, 2001-2010 and 2011-2018. Two main conclusions stand out. First, there has been a clear contraction of the manufacturing sector during the past three decades. The manufacturing employment share fell from 44.6% to 22.6% between the late 80s and the new century's second decade (i.e., a drop of 21.9 percentage points). Second, the manufacturing contraction was offset by expanding the wholesale and retail trade, accommodation and food services, and real estate, renting, and business support services sectors. Yet, the latter raises the most (from 3.9% to 17.2% between 1985-1990 and 2010-2018).

Table 4.1 Eurostat classification of Knowledge Intensive Activities (KIA), Business industries (Based on the Statistical classification of economic activities in the European Community (NACE) Rev. 1.1/CAE Rev. 2)

CODE	*DESCRIPTION*
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Manufacture of chemicals and chemical products
30	Manufacture of office machinery and computers
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
62	Air transport
65	Financial intermediation, except insurance and pension funding
66	Insurance and pension funding, except compulsory social security
67	Activities auxiliary to financial intermediation
72	Computer and related activities
73	Research and development
74	Other business activities
92	Recreational, cultural and sporting activities

Note: According to Eurostat, "an activity is classified as knowledge-intensive if tertiary educated persons employed (according to ISCED'97, levels 5+6) represent more than 33% of the total employment in that activity. The definition is based on the average number of employed persons aged 25-64 at aggregated EU-27 level in 2006, 2007, and 2008 according to NACE Rev. 1.1 at 2-digit (equivalent to CAE Rev. 2.1), using EU Labour Force Survey data."

Several studies have indicated that Portugal has transitioned from an industrial to a service economy. However, we can obtain misleading results without a common industry classification. After sector homogenization, I confirm those results, but this time with an industrial evolution that relies on a consistent classification (i.e., CAE Rev. 2).

Figure 4.1 shows the evolution of knowledge-intensive activities (KIA) employment share. This sector has experienced a significant expansion during the sample interval, going from 11.3% to 21.2% of total employment between 1985-1990 and 2011-2018. Moreover, it is important to highlight that the subsector that explains most of the expansion in the KIA sector is 'business support activities,' which increased from 3.3% in 1985-1990 to 13.9% in 2011-2018. Hence, this subsector has likely benefited from a new value chain distribution and ICT processes that simplify business management. Figure 4.1 also highlights the reduction in knowledge-intensive manufacturing activities (from 2.9% to 1% between 1985-

1990 and 2011-2018) and the non-negligible development of the ‘computers and related activities’ subsector (from 0.1 % to 1.9%).

Table 4.2 Employment-share by time-consistent aggregate sectors

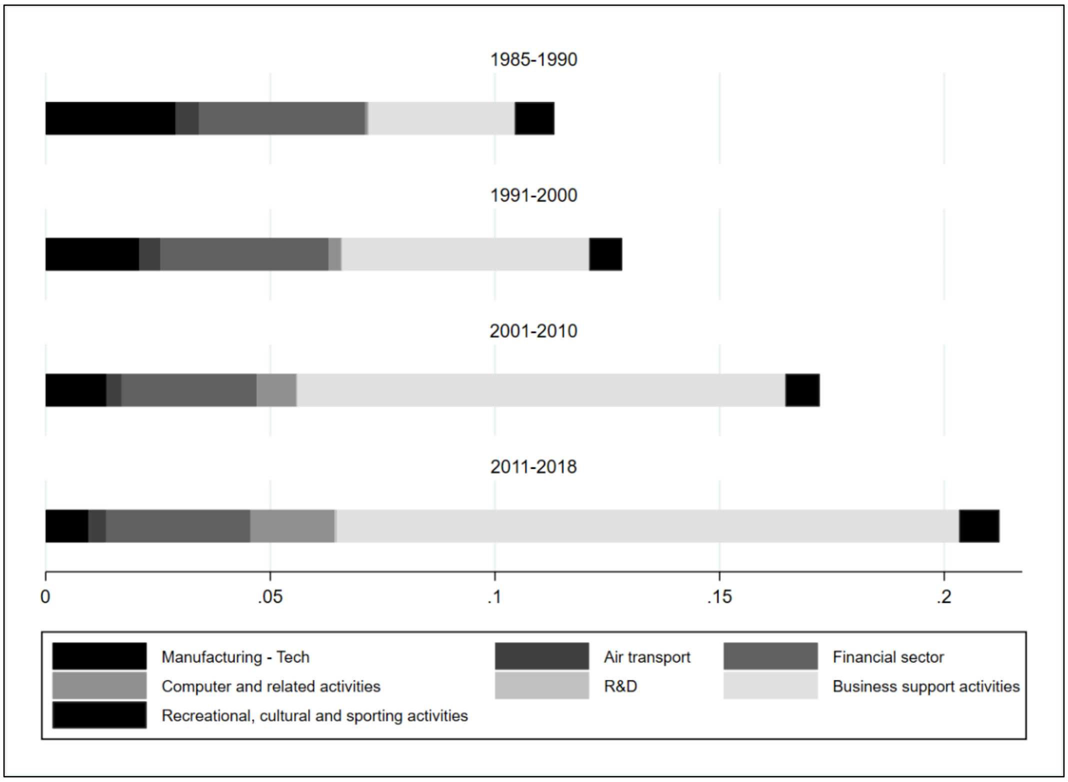
Sectors	*1985-1990*	*1991-2000*	*2001-2010*	*2011-2018*	*2011-2018 minus 1985-1990 (p.p.)*
Primary sector (A, B & C)	3,0%	2,7%	2,6%	2,8%	-0,2
Manufacturing	44,6%	38,2%	26,4%	22,6%	-21,9
Electricity, gas, and water	1,3%	0,9%	0,5%	0,6%	-0,8
Construction	8,7%	10,4%	13,2%	8,5%	-0,1
Wholesale and retail trade	17,2%	20,5%	21,7%	21,7%	4,4
Accommodation and food services	4,8%	6,4%	7,6%	8,6%	3,8
Transportation, storage and communications	7,5%	6,4%	5,9%	6,3%	-1,2
Financial sector	3,7%	3,7%	3,0%	3,2%	-0,5
Real estate and business support services	3,9%	6,6%	13,1%	17,2%	13,2
Public administration, defence, education, and health (L, M & N)	3,1%	2,5%	3,7%	5,9%	2,8
Other collective and personal services	2,1%	1,6%	2,2%	2,5%	0,5
Other sectors (P & Q)	0,0%	0,0%	0,0%	0,0%	0,0

Note: Industries are classified on a time-consistent CAE Rev. 2 basis. Own computations.

The analysis focuses on the industrial and non-financial market services sectors. Accordingly, the selected sample contains manufacturing, construction, wholesale and retail trade, accommodation and food services, and real estate, renting, and business support services sectors, as well as travel agencies and transport-related services (code 63) and recreational, cultural and sports activities (code 92) subsectors. The financial, utilities, education, public administration, health, international organisations sectors, and the entire primary sector (agriculture and extractive industries) were therefore excluded. I have also removed all the remaining personal services subsectors (codes 90, 91, and 93).

As a result, the final sample comprises an unbalanced panel of 896,827 firms, making up 7,534,119 year-firm observations containing new, continuing, and exiting firms. Thus, the target population includes all non-financial enterprises operating in the manufacturing and service sectors with at least one employee.

Figure 4.1 The employment share in the KIA sector by subsectors



Note: Knowledge-intensive activities are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis.

4.2 Measuring firm efficiency

4.2.1 Revenue labour productivity

Productivity plays a central role as its growth is expected to be one of the main outcomes of creative destruction. Depending on the assumptions we are willing to make on cost functions, the efficiency variable is typically measured through labour productivity or total factor productivity (TFP). The neoclassical approach assumes convex cost curves and substitution between capital and labour. Hence, a 'Cobb-Douglas function' characterise firm production, and the selected efficiency measure is TFP—usually estimated as the Solow regression residual (Decker et al., 2018; Syverson, 2011). In turn, some heterodox approaches, particularly evolutionists and post-Keynesians, postulate that capital and labour are predominantly complementary inputs, and their production ratio relies on a fixed technical coefficient—at least, up to the full capacity level (Dosi & Grazzi, 2006; Lavoie, 2014).[39] As a result, a 'Leontief function' explains output relations, and the preferred efficiency measure is given by labour productivity (calculated as output per unit of labour). The evidence suggests, however, that the two variables tend to be strongly correlated (Foster et al., 2001).

Due to data restrictions, the primary measure is labour productivity. It is computed as the ratio between *gross* output and labour input. Specifically, I estimate labour productivity employing the QP dataset as the ratio between real sales and the number of employees. This variable is known as Revenue Labour Productivity (RLP). Although labour productivity would ideally be calculated as net output per labour unit, previous evidence shows that RLP would track value-added per worker quite well in within-industry analyses (Foster et al., 2001). On the other hand, as detailed industry deflators are not available for the sample period, much less for the previous industry classification (i.e., CAE Rev. 2), I use the GDP deflator index extracted from the AMECO database to deflate sales (2015=100). However, all estimates implicitly control for sectorial prices since RLP is measured relative to the average industry level (2-digit).

Since the pre-2010 companies reported sales for $t-1$ in the period t, employment in t corresponds to the sales level in $t+1$ between 1986 and 2009. To deal with this issue, I first harmonised the reported information's timing by exploiting the longitudinal nature of the data. Second, using the common business identifiers, I merged the SCIE data with QP to assign the missing values since 2004 on (the first year collected by the SCIE). However, the remaining missing values are unlikely to be randomly distributed: i) between 1985-2003, there is no information on the companies that appear in the data for only one year and those that closed temporarily or permanently.[40] And ii) there is no information on companies outside the SCIE for merged information since 2004. Hence, following Foster et al. (2016), I have estimated propensity score weights for each firm-year observation so that the subsample of firms with revenue information is representative of the population.[41] First, I

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[39] Although evolutionary technologies are described as recipes rather than input-output relations (Dosi & Grazzi, 2006).

[40] This limitation affects both the estimation of the RLP, and the market concentration measures used in the 6th chapter. In the latter case, it is most likely that the estimates are upward biased between 1985 and 2003 since the ratio's denominator would be underestimated. However, in that case, there would be a downward bias, rather than an upward bias, in the concentration change over the period.

[41] Estimating probabilistic models separately for each year allows for considering the changing nature of samples.

apply logistic regressions to predict the presence of firms with revenue data in the population of QP companies. Then, I use the resulting (inverse) propensity scores as sampling weights in all estimations that include sales and revenue productivity. The inverse probability weights are explicitly computed as follows:

$$ipw = \frac{1}{E[P(Y = 1|\boldsymbol{Z})]} \; if \; Y = 1 \tag{4.1}$$

$$ipw = \frac{1}{1-E[P(Y = 1|\boldsymbol{Z})]} \; if \; Y = 0 \tag{4.2}$$

where 'ipw' denotes the inverse probability weight, and 'Y' is the binary dependent variable, equal to 1 for firms with revenue data and zero otherwise. The predictor matrix '**Z**' contains dummies variables for start-ups, multi-plant firms and single-owner companies; the average number of workers between 't' and '$\mathrm{t}-1$''; Davis et al. (1996) employment growth rate (computation explained in Chapter 5); and industry and location dummies. Such inverse probability weights enable the weighted sample to almost replicate the QP's size, growth, and industry distributions.

However, the decisive test for the variable's reliability lies in the ability to aggregate and replicate the productivity profile of the Portuguese economy over the last 30 years. So, firstly, I aggregate productivity at the industrial level (2 digits) as follows:

$$P_{s,t} = \sum_{i \in s} \theta_{i,t} p_{i,t} \tag{4.3}$$

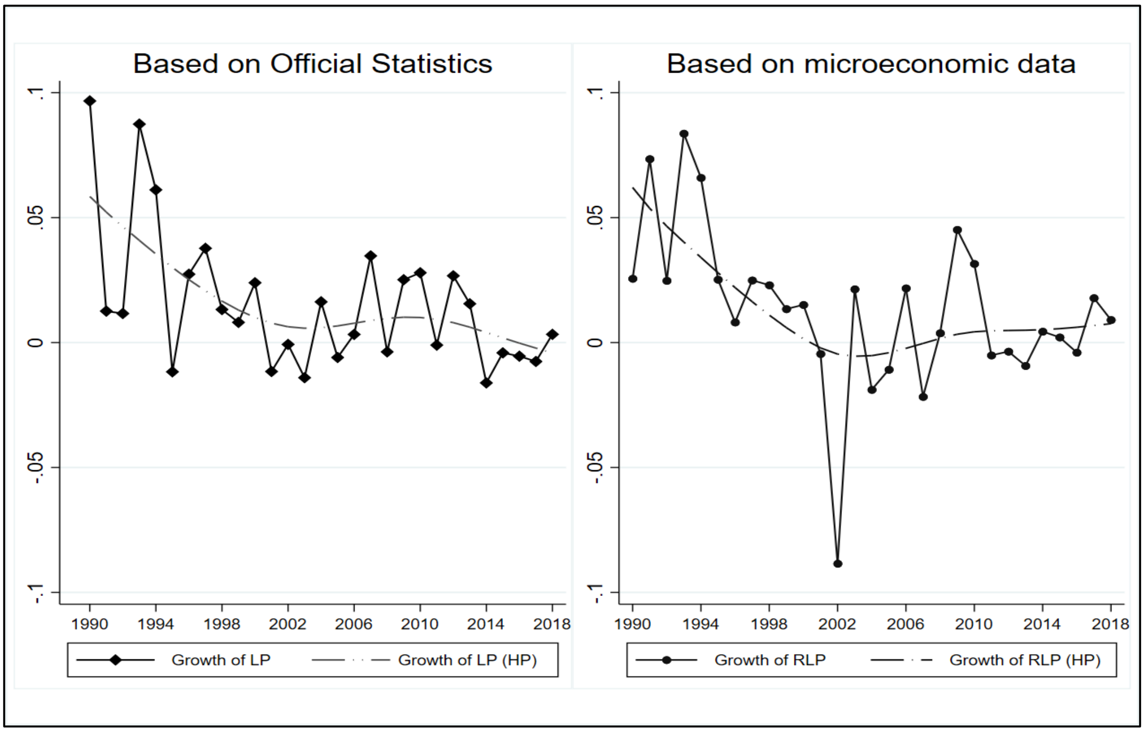
where $P_{s,t}$ denotes the log productivity of industry s in period t; $\theta_{i,t}$ is the sampling-weighted employment share of the firm i; and $p_{i,t}$ denotes the log revenue labour productivity of firm i. After that, following Decker et al. (2017), I used fixed weights to aggregate the industry estimates at the economy-wide level, namely the employment share of industry 's' in the entire sample interval.

To compare the evolution of this variable with a measure estimated from official sources, I extracted the information on gross value added and employment by the corresponding industry from INE. Subsequently, I computed the sectoral productivity after deflating the value-added (using the GDP deflators obtained from AMECO). Finally, I aggregate productivity at the economy level (official productivity, henceforth), also using the sectoral share of total employment over the entire interval as fixed weights. Two caveats must, however, be considered. First, *official productivity* relies on value-added, while QP productivity is based on sales. Second, sectors were classified using different methodologies.

For instance, in the case of *official productivity*, I could not exclude utilities and extractive sectors (such as mining), as they are within the same category as manufacturing.

Figure 4.2 shows that the microdata approach of aggregate productivity closely follows the evolution of official productivity, except for the (outlier) year 2002.[42] In both cases, the high productivity growth during the 1990s and its stagnation since 2000 stand out.

Figure 4.2 The Evolution of Labour Productivity during 1990-2018



Note: The series show the evolution of Labour Productivity in the manufacturing and non-financial market services sectors. Official productivity is a value-added-based measure, while labour productivity calculated from QP data is a revenue-based measure. Official productivity also includes utilities and extractive sectors. The sectoral information on added value and employment for calculating official productivity is extracted from the INE. Industry productivity is defined as employment-weighted firm labour productivity. To compute economy-wide productivity, the sectoral share in total employment over the entire interval is used as fixed weights.

Finally, it is worth noting that I perform robustness tests using TFP, calculated using the SCIE dataset for the available period (i.e., 2004-2018). Next, I explain the corresponding estimation process.

[42] In 2002, after a legal reform, the INE expanded the scope of data collection. This alteration entailed, on the one hand, the inclusion of the services of the Central, Regional and Local Administration and the public institutes employing workers on an individual contract basis (including public enterprises operating in the productive sector). On the other hand, employers with more than ten employees were gradually required to submit information by computer (during a transition period of three years, depending on the firm size) (GEP, 2022). Accordingly, the 2002 data is likely affected by errors or duplication in information processing resulting from these alterations.

4.2.2 *Total factor productivity*[43]

The estimation of Total Factor Productivity (TFP) is based on a neoclassical Cobb-Douglas production function $\mathrm{Q_{i,t}} = \mathrm{A_{i,t}K_{i,t}^{\alpha_K}L_{i,t}^{\alpha_L}M_{i,t}^{\alpha_M}}$ for each industry (2-digit CAE Rev. 2). In its logarithmic form, we have:

$$\ln \mathrm{Q_{i,t}} = \alpha_0 + \alpha_\mathrm{K} \ \ln \mathrm{K_{i,t}} + \alpha_\mathrm{L} \ \ln \mathrm{L_{i,t}} + \alpha_\mathrm{M} \ln \mathrm{M_{i,t}} + \varepsilon_\mathrm{i,t}, \tag{4.4}$$

where $\mathrm{Q_{i,t}}$ is the real output of the firm *i* in year *t*, and $K_{i,t}$, $L_{i,t}$ and $M_{i,t}$ denote capital, labour, and materials, respectively; α_e is the associated elasticity for input e ($e \in \{K, L, M\}$). Accordingly, the (Hicks neutral) firm technology level is given by:

$$\ln(\mathrm{A_{i,t}}) = \alpha_0 + \varepsilon_\mathrm{i,t}, \tag{4.5}$$

where α_0 denotes the mean productivity across firms within the industry and over time, while $\varepsilon_{i,t}$ is the time- and firm-specific deviation from that mean. This deviation can, in turn, be broken down into a predictable component $\eta_{i,t}$ and an unobservable component—or measurement error—$\nu_{i,t}$ (i.i.d.). The equation of the production function turns out to be:

$$\ln \mathrm{Q_{i,t}} = \alpha_0 + \alpha_\mathrm{K} \ \ln \mathrm{K_{i,t}} + \alpha_\mathrm{L} \ \ln \mathrm{L_{i,t}} + \alpha_\mathrm{M} \ln \mathrm{M_{i,t}} + \eta_\mathrm{i,t} + \nu_\mathrm{i,t}, \tag{4.6}$$

In this framework, the firm technical efficiency is given by $TFP_{i,t} = \alpha_0 + \eta_{i,t}$.

However, as is well-known, estimating the production function by Ordinary Least Squares (OLS) typically yields inconsistent outcomes, essentially for four reasons. First, unobserved efficiency influences both the production and the level of the inputs (i.e., the covariance between productivity and factors of production is different from zero). This bias is known as ‘endogeneity of inputs’ or ‘simultaneity bias.’ Second, decisions on input choice in a given period are conditional on survival. Therefore, we can expect at least a correlation between unobserved efficiency and investment decisions. This bias is known as ‘endogeneity of attrition’ or ‘sample selection bias.’ Third, since revenue data are generally available instead of production quantity data, there is a likely correlation between firm price changes and input choice. This issue is known as ‘omitted price bias.’ Finally, if companies produce more than one product, the equation of estimating the production function is ill-specified.

[43] The introductory part of this section draws extensively on the surveys of Van Beveren (2012) and Watson (Watson, 2018).

There are different methodologies to estimate TFP in the literature, although they generate similar results (Decker et al., 2018; Syverson, 2011). This inquiry applies the semi-parametric method proposed by Levinsohn and Petrin (2003), controlling for endogenous exit (Rovigatti et al., 2018). Levinsohn and Petrin (2003), following the estimation algorithm by Olley and Pakes (1996), use a control function approach that attempts to model the simultaneity between TFP realizations and input choices. In particular, it uses intermediate inputs as a proxy variable for the unobservable shocks.

The variables of production, capital and materials required to estimate TFP are only available in the SCIE dataset, whose survey period began in 2004. Yet, companies are classified according to CAE Rev. 3 in SCIE, while the industrial classification used in the homogenization process was CAE Rev. 2. Thus, I combine SCIE and QP so that the estimated production function corresponds to each 2-digit time-consistent industry that lies in the QP.[44]

The output corresponds to gross sales less the value of purchases of goods for resale (i.e., only trade margins are included), adjusted for changes in the inventory of final goods, self-consumption of own production, and other operating revenues. Labour corresponds to employment in the reference month. Real capital is measured using a perpetual inventory method to the change in total real assets. In detail, for the first year of a firm, I deflate the book value of total net assets by the GDP deflator index of that year to derive the capital stock K_t. For successive years, if the assets rise, then the increase is deflated by the GDP deflator index of the current year and added to K_{t-1} to yield the corresponding K_t. If it declines, K_t is reduced proportionately.

I use the GDP deflator index, extracted from the AMECO database, to deflate the gross output, capital and materials (2015=100). Nevertheless, all estimates implicitly control for industry prices since TFP is calculated relative to the average annual level in each 2-digit industry. Moreover, since the productivity variable is a revenue measure, firm-level prices are embedded. Thus, TFP estimation reflects technical efficiency and demand shocks.

[44] Chapter 7, dedicated to exit barriers, uses the SCIE dataset as the only source of information. Hence, the reference classification is CAE Rev. 3, for which 2-digit industrial deflators are available (taken from the INE).

Finally, I apply propensity score weights to account for imperfect matches between SCIE and QP.[45] I estimate these propensity scores separately for each year and use them as (inverse) sampling weights in all estimations.

[45] In this setting, the dependent binary variable takes the value of 1 for all SCIE companies that appear in the QP and zero otherwise. The matrix of predictors contains dummies for new firms, multi-plant firms, and single owner firms; the number of workers; employment growth (Davis et al. (1996) rate); and industry and location dummies.

5 The rise and decline of business dynamism in Portugal during 1986-2018

5.1 Methodology

This chapter starts with the computation of entry and exit rates. Entry is flagged the first time the company reports positive employment, which implies that reopenings are excluded. In turn, the exit of a given firm is identified in the year following the last time the company reports positive employment. Thus, temporary closings are not considered exits. QP also has information at the plant level, but plant identifiers depend directly on firm identifiers. This means that it is impossible to distinguish between an involuntary closure and the change resulting from a merger or acquisition, as the plant identifier will change accordingly. However, previous evidence suggests that these events are very unusual in the Portuguese economy (Mata & Portugal, 2004), so the estimates are unlikely to be affected by the selected procedure. The entry (exit) rate is the ratio between entering (exiting) firms and the total number of enterprises, given by the sum of entering, continuing, and exiting firms.

Subsequently, I estimate job flows (i.e., creation, destruction, and reallocation), which are just weighted sums of employment growth rates at the firm level for the various aggregation levels. To compute employment growth rates, it is followed the approach of Davis et al. (1996) calculated as follows:

$$\mathrm{g_{i,t}} = \frac{\mathrm{E_{i,t}} - \mathrm{E_{i,t-1}}}{\mathrm{X_{i,t}}}, \tag{5.1}$$

where, $g_{i,t}$ is the employment growth rate of firm *i* in period *t*; $E_{i,t}$ denotes employment and $X_{i,t}$ is the average employment between *t* and *t-1* so that $X_{i,t} = \frac{E_{i,t}+E_{i,t-1}}{2}$. As Haltiwanger et al. (Haltiwanger et al., 2013) point out, using the average employment as a denominator aims to neutralise the "regression-to-the-mean" bias. Specifically, since employment in *t* induces a downward bias and employment in *t-1* an upward bias, both effects are expected to cancel out. It is also worth noting that the Davis et al. rate's distribution is bounded between 2 (for entries and reopenings, in our case) and -2 (for exits and temporary closings).[46] Afterwards, following Haltiwanger et al. (2009), job flows are computed as follows:

[46] Although reopenings and temporary closures were excluded from the calculation of entry and exit rates, these events are still marked by growth rates equal to 2 and -2, respectively.

$$\mathrm{JCR}_{s,t} = \sum_{\substack{i\in s\\ g_{i,t}\geq 0}} \left(\frac{X_{i,t}}{X_{s,t}}\right) g_{i,t}\,; \tag{5.2}$$

$$\mathrm{JDR}_{s,t} = \sum_{\substack{i\in s\\ g_{i,t}<0}} \left(\frac{X_{i,t}}{X_{s,t}}\right) \left|g_{i,t}\right|\,; \tag{5.3}$$

$$\mathrm{JRR}_{s,t} = \mathrm{JCR}_{s,t} + \mathrm{JDR}_{s,t}; \tag{5.4}$$

where JCR, JDR and JRR denote the rates of job creation, destruction, and reallocation, respectively, and $X_{s,t} = \sum_{i\in s} X_{i,t}$; s denotes either the entire economy, size categories, age groups or sectors.[47]

Subsequently, I explore post-entry dynamics through survival analysis using non-parametric and semi-parametric techniques. Here, I observe the behaviour of new firm cohorts born from 1986 onwards. The failure event corresponds to exiting the market in t+1. The age is constructed based on the entry year and reports the survival time and whether failure or censoring occurs in each period. Once the survival data is declared, the life expectancy of entrants is explored at aggregated and disaggregated levels. Since the data is window-censored, the expected life expectancy corresponds to the extended mean of the survival spell, computed by extending the Kaplan-Meier product-limit survival curve to zero. I seek to compare the survival chances of a typical entrant during the late 1980s (1986-1990), the 1990s (1991-2000), the first (2001-2010) and the second (2011-2017) decades of the new century.[48]

Next, I examine the employment-weighted growth rate distribution. It is observed, in particular, the performance of young firms (under five years), compared with mature firms, through the inspection of the dispersion and skewness statistics.[49] The dispersion is calculated as the difference between the 90th and 10th percentiles of the employment-weighted distribution, while the skewness is calculated as the relationship between the 90-50 and 50-10 differentials. The 90-50 and 50-10 differentials denote the distance between the 90th and 50th percentiles and the 50th and 10th percentiles, respectively.

To assess the ability of young firms to expand, I calculate the corresponding annual share of aggregate employment. The typical performance of a high-growth firm (HGF) is observed

[47] The methodology closely follows the contributions by Haltiwanger et al. (2009) and Decker et al. (2016).

[48] Entering 2018 companies were excluded as this cohort would only be one year old.

[49] Given that age depends directly on the entry event, it is only possible to distinguish young companies from the mature ones since 1990.

by estimating the 90th percentile growth rate. Creative destruction does not necessarily require many entrants; the key aspect is the real chance of challenging industrial leaders. Innovative entrepreneurship then requires favourable conditions in the ex-ante and ex-post entry stages, especially concerning technology, finance, and the prevalence of a competitive environment. As a result, studying the behaviour of a typical young HGF is critical to observe how the quality of entrepreneurship and mobility barriers have evolved.

The long sample period allows us to isolate the effect of the business cycle. Thus, to separate the time series into trend and cyclic components, I apply the Hodrick-Prescott (HP) filter. Given the annual nature of the information, the smoothing parameter is set to 100. Finally, I pay special attention to intersectoral assessments according to the knowledge intensity level, using the Eurostat classification explained in chapter 4.

5.2 Estimation results

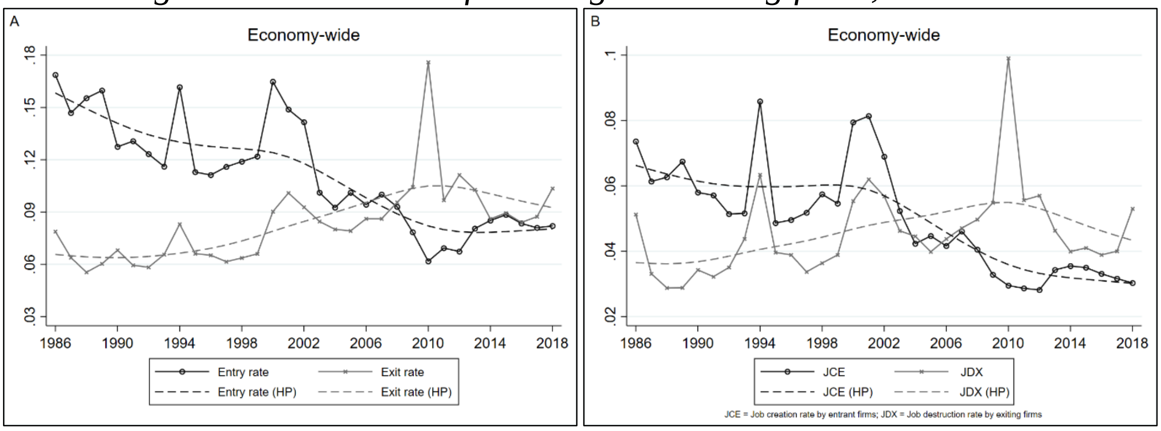
5.2.1 Entry, exit, and job flows

The new technological paradigm linked to the ICT revolution emerged in the early 80s. It is also concurrent with Portugal's adhesion to the European Union and the consequent currency change and enlargement of the trade borders. It is, therefore, very likely that the observed business dynamics reflect both the emergence of new markets (and the decline of others) and how surviving markets adapted to the new context (altering, for example, the productive trajectories of the past).

As mentioned, technological paradigms set the limits of the pool of knowledge from which inventors draw to generate innovations so that each technological paradigm embodies the *technology of technical change* (Dosi & Nelson, 2010). On the other hand, industrial life cycle literature suggests that, beyond sectoral specificities, each phase of market evolution appears to follow specific common patterns. First, as Klepper (1997) and Geroski (1995) point out, product competition is expected to dominate in the embryonic industrial stage, with high uncertainty, intense entry, and low market volumes. Then, as the standard product is defined, production growth increases, while entry tends to slow down due to, for example, the preponderance of process innovation, which tends to favour large established firms. Finally, in the mature phase, production is likely to decelerate, entry is further reduced, market shares are stabilised, and innovation becomes less relevant, possibly replaced by a refinement of management and marketing practices.[50]

Having this in mind, I analyse (exclusively) the Hodrick-Prescott (HP) business dynamism trends, paying particular attention to the knowledge-intensive activities (KIA) sector. Panel A of Figure 5.1 shows that the entry rate has steadily fallen from 1986 to 2018. In contrast, although to a lesser extent, the exit rate has gradually increased. While entry and exit rates were about 16% and 7% in 1986, these rates reached 8% and 9% in 2018.[51] However, looking at job creation trends (panel B), we notice that the contribution of start-ups to job creation declines after 2000. The share of new firms remained relatively constant during the 1990s, suggesting that, despite the reduction in the flow of new companies, those that entered the market did so on a larger scale. Instead, the job creation by entrants fell sharply in the post-2000 period, from 6% in 2000 to about 3% in 2018. Finally, the net entry rate and the net job creation by entrants turned negative between 2004 and 2006, remaining so until 2018.

Figure 5.1 The share of entering and exiting firms, 1986-2018



Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms). The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

As technological paradigms evolve, inventiveness tends to dry up, and the *normally increasing dynamic returns* are expected to enter a declining phase (until a new paradigm emerges) (Nelson, 2008; Perez, 2010). As a result, since, in the long run, mature industries

[50] Robinson (1969) argued that the competitive mechanism tends to weaken as markets evolve, as scale and financial constraints begin to play a critical role. In that sense, she argued that, in the long run, competition takes more the form of competition in marketing, which has neither the strength to ensure that production growth goes hand-in-hand with technological progress nor the ability to keep real wages in line with productivity.

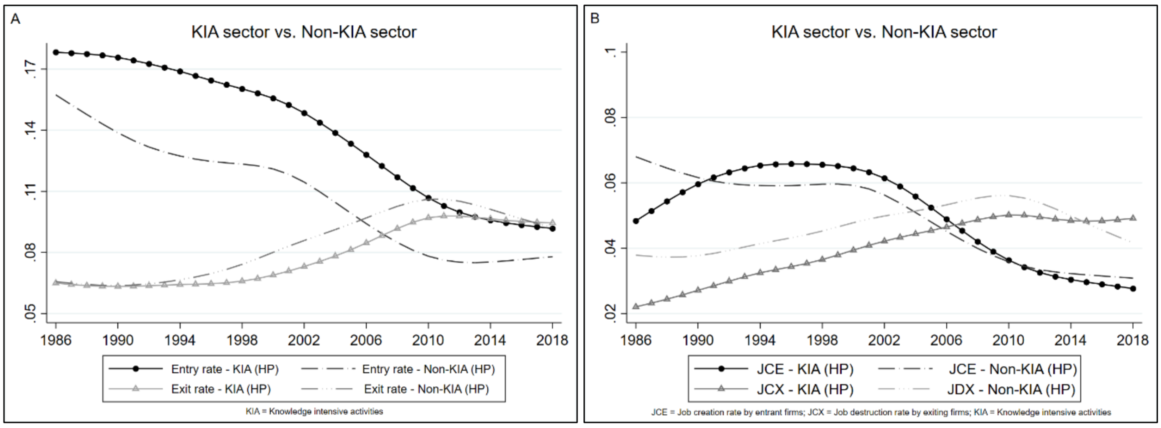
[51] Calvino et al. (2020) also reported a decrease, although more modest, in the formation of new companies in Portugal between 2002 and 2015. This indicates that results do not depend on the data or methodology used.

(where entry and survival are more stringent) outweigh nascent ones, it is relatively predictable that the entry rate has decreased and the exit rate has increased. However, a negative net firm formation and net job creation by entrants are expected to harm reallocation, market structure, and productivity growth. Moreover, it seems clear that entering markets has become increasingly difficult or less profitable over the past thirty years.

Furthermore, we could expect that in the non-traditional sectors (considered more technological and whose birth is associated with the emergence of ICT), the entry rate has been more vigorous, and the entry penetration into employment has been increasing during the late 20th century. When comparing the HP trends in entry and exit flows between the KIA sector and the rest of the industries (panel A of Figure 5.2), we observe that the entry rate was indeed higher in the KIA sector during the 1980s and 1990s. However, there has been a secular decline in firm creation in both sectors (KIA and Non-KIA). While the structural entry rate of the KIA (Non-KIA) sector was 17.95% (15.84%) in 1986, this rate dropped to 9.28% (7.89%) in 2018. The exit rate has also been slightly increased in both cases. Nevertheless, the net firm formation has become visibly negative only in the Non-KIA sector (since 2006).

Three facts stand out regarding job creation and destruction by the entrant and exiting firms in the KIA and Non-KIA sectors, as shown in panel B of Figure 5.2. *First*, the contribution of the entrant and exiting firms to job creation and destruction in the Non-KIA sector seem to replicate the patterns observed across the economy. Specifically, constant job creation during the 1990s and decreasing since 2000, along with a somewhat increasing destruction during 1986-2018. *Second*, concerning the KIA sector, we observe a job creation rate by entrants that is rather increasing from the late 1980s to the end of the 1990s, declining only after 2000. The growing contribution of start-ups to job creation up to 2000 is consistent with the industry lifecycle theory, as entrant companies are expected to play a critical role in the embryonic stages of emerging industries. *Third*, the net job creation by entrants has become negative even in the knowledge-intensive sector over the past decade.

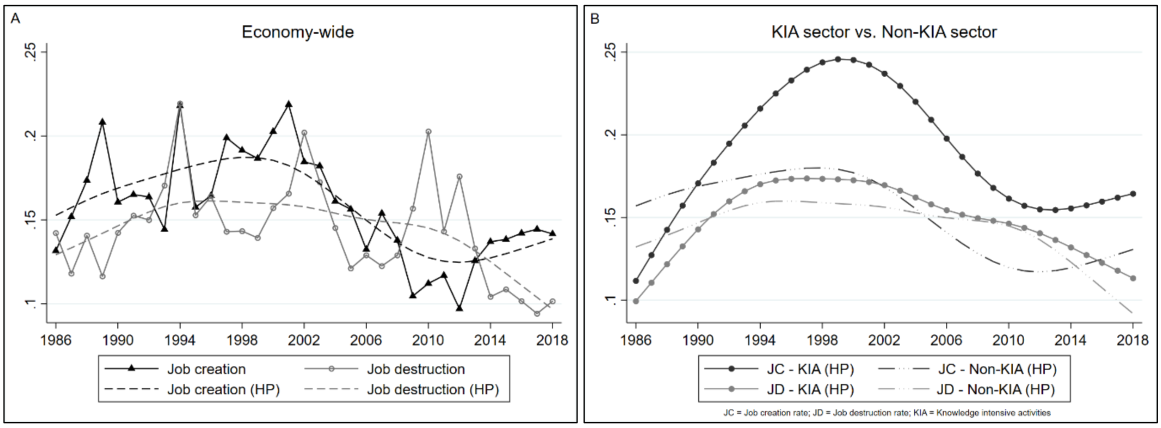
Figure 5.2 The share of entering and exiting firms by sector, 1986-2018



Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms) by each sector. The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms by each sector. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure 5.3 presents the job creation and destruction flows at the aggregate level (panel A) and disaggregated by knowledge intensity (panel B). As expected, these flows seem to mirror economic growth in Portugal. Thus, during the 1990s, job creation and destruction increased, with a highly positive net balance, particularly in the KIA sector. In fact, net job creation appears to be driven primarily by expanding knowledge-intensive industries. Specifically, while the average job creation and destruction rates in the KIA sector were 22.32% and 16.87% during 1991-2000, respectively, these rates were 17.67% and 15.76% in the Non-KIA sector, which resulted in a net job creation rate of nearly four p.p. higher in the KIA sector. However, both creation and destruction have fallen sharply since 2000. The KIA sector's decline is sudden: job creation increased from approximately 25% to 16% between 2000 and 2018, while job destruction was reduced from 17% to 11%. Furthermore, although net job creation has again become positive since 2014, this is mainly due to decreased destruction rather than increased gross creation.

Figure 5.3 Job creation and destruction rates, 1986-2018

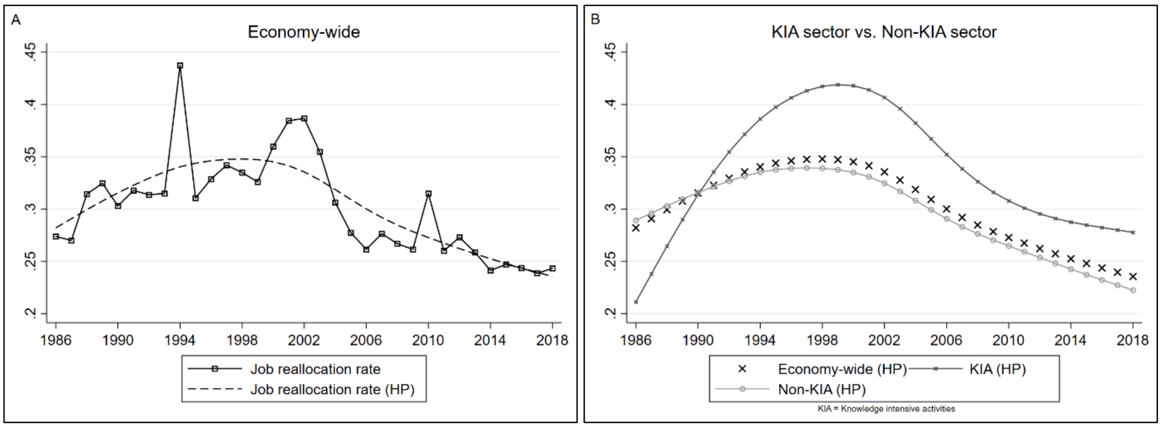


Note: The job creation (destruction) rate is computed as the employment-weighted average of the absolute value of employment-growth rates of all firms with non-negative (negative) growth rates, across the economy and by sector, left panel and right panel, respectively. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

The collapse of job creation and destruction flows led to a drastic drop in the reallocation rate during the new century. Figure 5.4 shows that job reallocation first showed an increasing pattern between 1986 and 2000, from 28% to about 35%. Job reallocation was also more intense in the KIA sector, whose rate increased from 21% in 1986 to 42% in 2000. Nevertheless, in the post-2000 period, there has been a secular decline in reallocation. The economy-wide job reallocation rate decreased from 35% in 2000 to 24% in 2018, while this rate declined from 42% to about 28% in the KIA sector (a reduction of 14 p.p.). In the disaggregated analysis by sectors of economic specialisation, shown in Figure A.7 of the Appendix section, we confirm that this sharp decline in reallocation has been ubiquitous in the post-2000 era.[52]

[52] In the Appendix A, we can observe the entry, exit, job creation, job destruction, and job reallocation rates in particular sectors, and the secular trends seem to follow a common pattern.

Figure 5.4 Job reallocation rate, 1986-2018



Note: The job reallocation rate is equal to the sum of the rates of job creation and job destruction, across the economy (left panel) and by sector (right panel). Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

5.2.2 Post-entry dynamics and high-growth young firms

In the previous section, we observed that there had been a secular weakening in business formation and a declining impact of new firms on job creation over the past three decades. However, it remains to be understood whether the entrants were more or less likely to survive and expand; and whether a deterioration in post-entry growth accompanied the decline in the entrepreneurship rate.

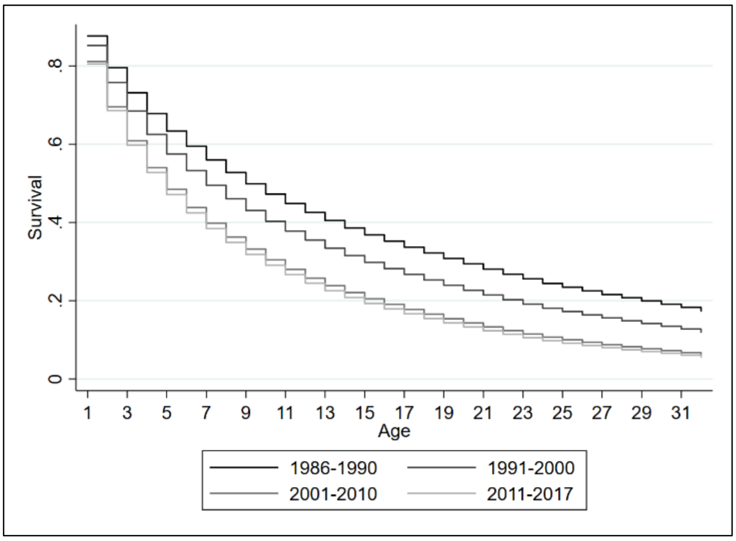
This subsection started by examining the survival probability of entrant companies for the periods 1985-1990, 1991-2000, 2001-2010, and 2011-2017. To this end, I have estimated the conditional survival function for each interval using semiparametric survival modelling.[53] Previous evidence suggests that the post-entry phase of young firms is characterised by "up-or-out" dynamics, in which most infant firms exit during the first five years of life (Decker et al., 2014). This high early mortality rate appears to result from an overpopulated entry of "muppet" enterprises, which market selection mechanisms quickly expel. However, a low probability of survival may also result from mobility barriers, as they are more severe for young and small firms.

In Figure 5.5, we note not only that the survival likelihood of entrants is indeed low and decreasing but also that their exit hazard has increased every decade. Thus, for example,

[53] I apply the semi-parametric Cox Proportional Hazard model, where the unique regressor is a categorical variable containing each interval. I thus control by the baseline hazard function, $h_0(t)$, while the survival function of each period is estimated according to the same time range. To deal with 'tied failures', derived from annual information, I use the Breslow approach (Cleves et al., 2010).

while a five-year-old company has an average survival probability of approximately 63% during 1986-1990, its 2011-2017 counterpart has a survival chance of only 47%. Therefore, these results indicate that not only has there been a reduction in the entry of new companies, but also nascent firms have faced an increasing failure risk. In fact, as Table 5.1 shows, the estimated life expectancy of a typical entrant is reduced by more than two years, from 11.42 years in 1986-1990 to 9.26 years in 2011-2017. On the other hand, start-ups have a longer expected survival time in the KIA sector than in the Non-KIA sector. But, in both sectors, the life expectancy of entrants has decreased, this reduction being relatively higher in the latter.[54]

Figure 5.5 Conditional survival function of new firms by periods



Note: The graph shows the estimated survival function of entrant firms for the periods 1986-1990, 1991-2000, 2001-2010, 2011-2018, conditional on the baseline hazard curve (from the Cox-regression). The survival function reports the probability of surviving beyond 't'.

[54] Table 2 also shows the entrants' survival time by sector of economic specialization. Except for manufacturing, and the cultural and sporting activities subsector, the survival spell is reduced in all sectors.

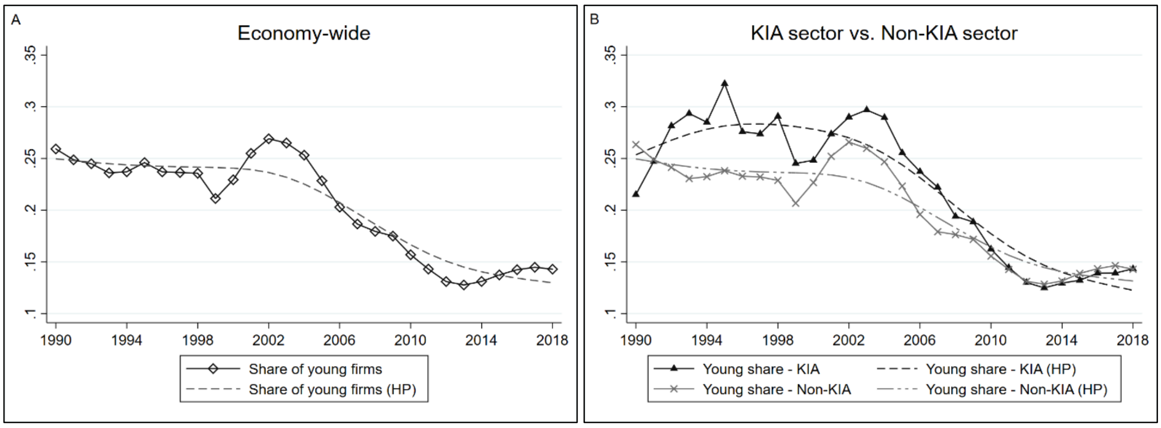
Table 5.1 Estimated survival time of entrants by periods

	1986-2017	1986-1990	1991-2000	2001-2010	2011-2017	1986-1990 Vs 2011-2017
Economy-wide	10,49	11,42	11,39	9,45	9,26	-19%
By knowledge intensity of the industry						
Knowledge-intensive activities	11,73	11,51	13,66	10,63	10,48	-9%
Non-knowledge-intensive activities	10,35	11,41	11,23	9,30	9,07	-20%
By economic specialisation of the industry						
Sector						
Manufacturing	11,77	11,18	10,91	10,27	11,84	6%
Construction	9,25	11,17	10,89	8,23	8,44	-24%
Wholesale and retail trade	10,77	11,85	11,45	9,77	9,41	-21%
Accommodation and food services	9,39	10,42	11,26	8,77	7,54	-28%
Real estate, renting and business support services	11,23	13,52	14,05	10,17	10,15	-25%
Subsectors						
Travel agencies and transport-related services	14,45	22,41	16,16	14,36	11,42	-49%
Recreational, cultural and sporting activities	9,38	6,26	9,45	8,69	9,08	45%

Note: The reported values denote extended means of the survival spell of entrant firms (in years), using the method of Klein and Moeschberger (2003), computed by extending the Kaplan-Meier product-limit survival curve to zero. Knowledge-intensive activities (KIA) are classified using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis.

Figure 5.6 shows the evolution of the proportion of young firms in aggregate employment. In line with the information observed in entrant firms, we observe that the economy-wide employment share of young companies remains relatively constant until the late 90s. Then, however, the proportion of young enterprises in total employment began to fall in 2002, with a peak of about 27% and then a sharp decline to about 14% in 2018. Regarding the knowledge intensity level of industries, notice that the proportion of young firms in the KIA sector's employment has an instead rising slope until 2000. Yet, this share falls in the post-2000 era, from 30% in 2003 to 14% in 2018. In the Non-KIA sector, young firms maintained a relatively constant share until the 1990s. But after 2000 it also started to decline. The results suggest that lower entry and higher mortality of infant firms weakened the position of young companies in aggregate employment so that overall ageing of industries is likely to have taken place. In Figure A.8 in the Appendix, I confirm these findings in the analysis by sector of economic specialisation.

Figure 5.6 The employment-share of young firms, 1990-2018

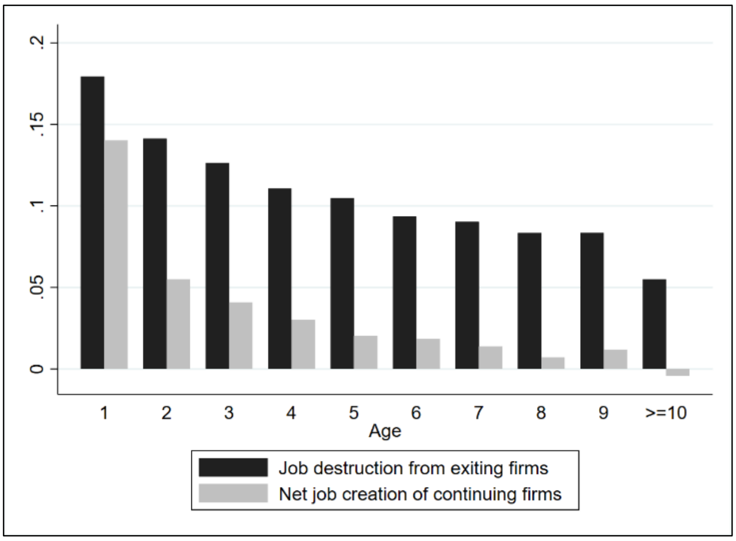


Note: The share of employment at young firms is calculated as the ratio of total (average) employment in young companies to total (average) employment in all firms, across the economy (left panel) and by sector (right panel). Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure 5.7 characterises the post-entry dynamics and the aggregate contribution of young companies. In particular, I estimate the job destruction from exiting firms versus the net job creation of continuing companies (i.e., employment-weighted average net growth) for each year of age (excluding newborn firms whose gross and net job creation are equal).[55] In line with the results reported by Decker et al. (2014), we confirm an intense "up-or-out" dynamic of young firms. In other words, they exhibit high mortality along with strong growth of survivors. Indeed, conditioned on survival, young firms show a much higher net growth rate than their mature counterparts. For instance, a five-year-old surviving firm has an employment-weighted net growth rate that is 2.5 p.p. higher than a 10-year-old firm (where net growth is even negative). It is then young firms that generate the greatest contributions to net job creation.

[55] I have calculated the statistics since 1995, as only from that year can we differentiate a company with 10 years or more (the age depends on the entry year).

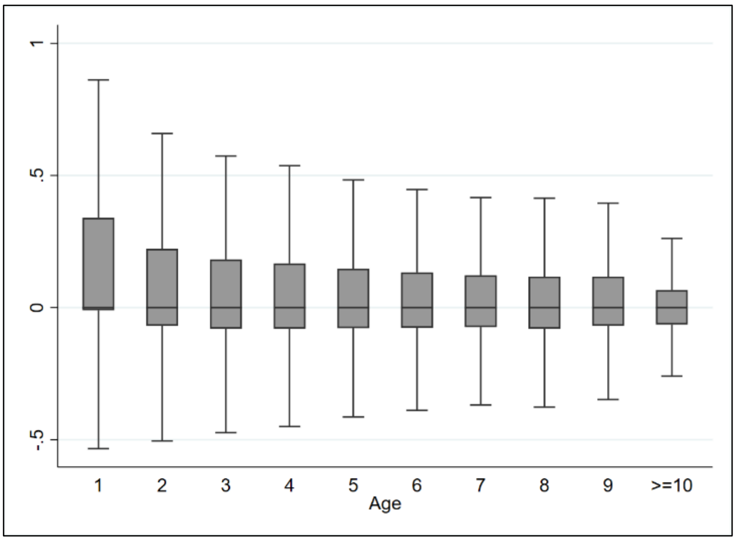
Figure 5.7 The post-entry dynamics of net creation and destruction, 1995-2018



Note: The figure shows the net employment growth rate of continuing firms and job destruction rate by exiting firms for companies age 1 and older. The net job creation rate is computed as the employment-weighted average of the employment-growth rates of continuing firms in each age cell. The job destruction rate by exiting firms is defined as the employment-weighted average of the employment-growth rates of exiting firms in each age cell. Pooled data from 1995 to 2018.

Nonetheless, as Decker et al. (2014) point out, young companies' average net growth rate masks much heterogeneity. Figure 5.8 shows that surviving firms' median net growth rate is close to zero at all ages. Yet, the distribution of young firms exhibits a greater dispersion—a higher interquartile range and greater distance between the maximum and minimum values of the boxplot—and a greater positive skewness—the distance between the maximum value and the median is greater than the distance between the median and the minimum value. Notice also that the dispersion and positive-skewness of the employment-weighted growth rate distribution are inversely proportional to the firm age. The distribution of a typical company of 10 years or more is practically symmetrical. Accordingly, young firms' high average net growth rate is skewed by those in the distribution's right tail. For this reason, the largest contribution of entrepreneurship to creative destruction is expected to come from young, high-growth firms.

Figure 5.8 The growth rate distribution by firm age, 1995-2018

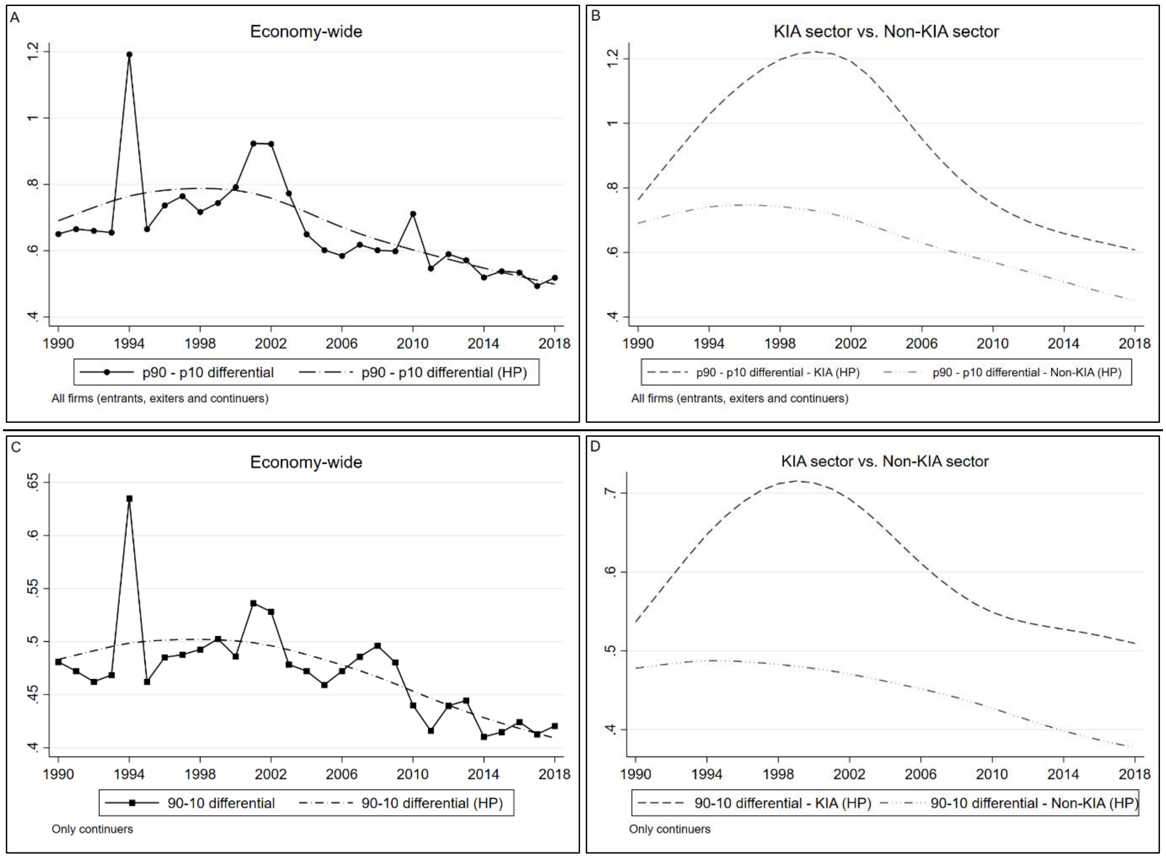


Note: The figure shows the employment-weighted box-and-whisker plot for continuing firms age 1 and older. Pooled data from 1995 to 2018.

Against this backdrop, it is critical to analyse the evolution of the growth rate distribution's dispersion and skewness and the typical growth of a high-growth firm (HGF), especially for young firms. To this end, Figure 5.9 presents the evolution of the differential 90-10 of the employment-weighted growth rate distribution at the aggregate level (panel A for all firms and panel C for continuing firms) and disaggregated by knowledge intensity (panel B for all firms and panel D for continuing firms). In line with the reallocation patterns, the analysis reveals an economy-wide dispersion that increases until the late 90s and declines after that. This growing dispersion of the first fifteen years of exploration is also driven by the emerging KIA industries' dynamism, whose dispersion was noticeably higher in the late 20th century. Nevertheless, the growth rates' dispersion of the KIA sector declined in the post-2000 era, reaching a 90-10 differential similar to that of 1990. It is important to note that the dispersion patterns for all and continuing firms, although with different magnitudes, follow a similar trajectory. Therefore, alterations in the distribution's dispersion seem not to be driven by the observed entry and exit rate changes.[56]

[56] By definition, the growth rates of entrant and exiting firms are equal to 2 and -2, which alters the magnitudes of the trend values.

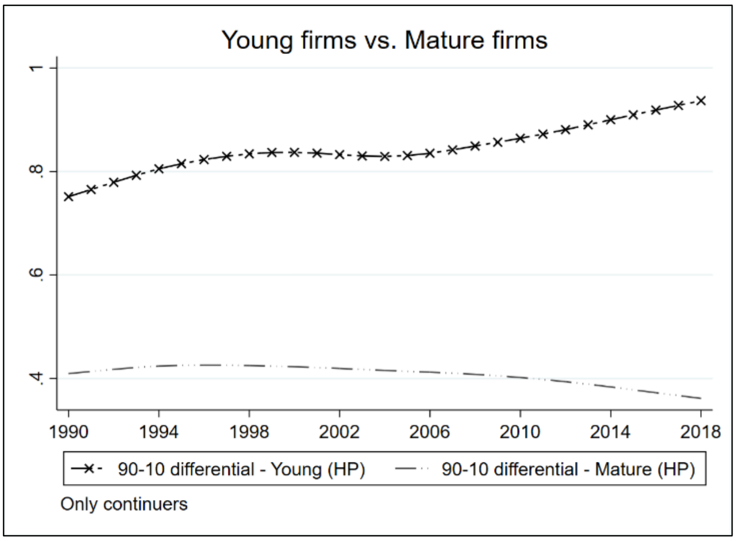
Figure 5.9 The dispersion of the employment-weighted growth rate distribution, 1990-2018



Note: The 90-10 differential is defined as the difference between the 90th and 10th percentiles of the employment-weighted distribution of employment growth rates for all (upper panels) and continuing (lower panels) firms. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

The dispersion of the growth rate distribution differentiated by age groups shows opposing trends (Figure 5.10). The dispersion patterns of mature firms are similar to those observed throughout the economy. Instead, the dispersion of young companies increases over the entire 1990-2018 period. Specifically, the 90-10 differential of young firms' employment-weighted growth rate distribution increased from 0.74 p.p. to 0.95 p.p. between 1990 and 2018 (i.e., 21 p.p.). Unlike what happened in the overall economy, the job reallocation within young firms appears to have been increasingly intense during 1990-2018.

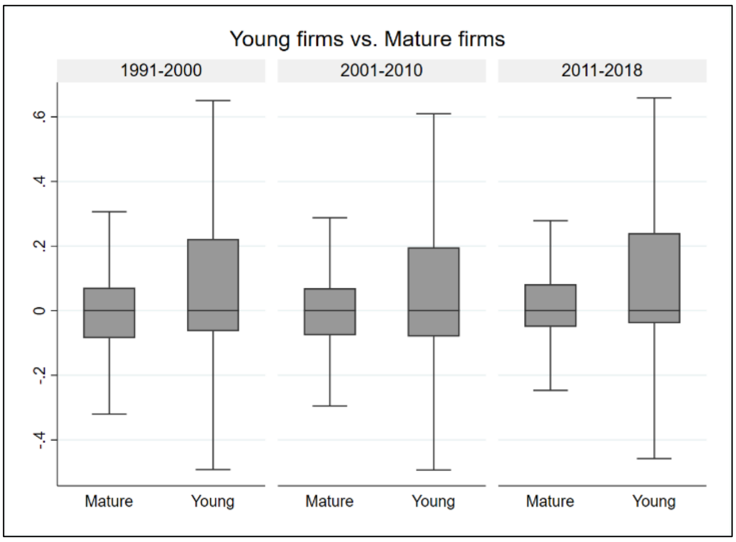
Figure 5.10 The dispersion of the employment-weighted growth rate distribution by age, 1990-2018



Note: The 90-10 differential is defined as the difference between the 90th and 10th percentiles of the employment-weighted distribution of employment growth rates for continuing firms by age category. Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

In Figure 5.11, we further observe that this higher dispersion has not occurred due to a greater distance from the left tail (where laggard firms are located); it is due to a distribution shift to the right. The box and whisker diagram, differentiated by a decade of analysis, shows that young firms in 2011-2018 had a higher performance than in the previous decades (1991-2000 and 2001-2010). The diagram's maximum (minimum) value is at a larger (shorter) distance from the median during 2011-2018. These results indicate that young firms have performed better and better and that those on the right tail have been growing even faster. Regarding mature firms, the diagram confirms that there has been a clear contraction of the dispersion, whose tails are now much closer to the median (therefore, neither so exceptional nor so deficient). Finally, laggard mature companies of the 2011-2018 interval appear to grow *less slowly* than their counterparts in the previous decades.

Figure 5.11 The growth rate distribution by age category and by period

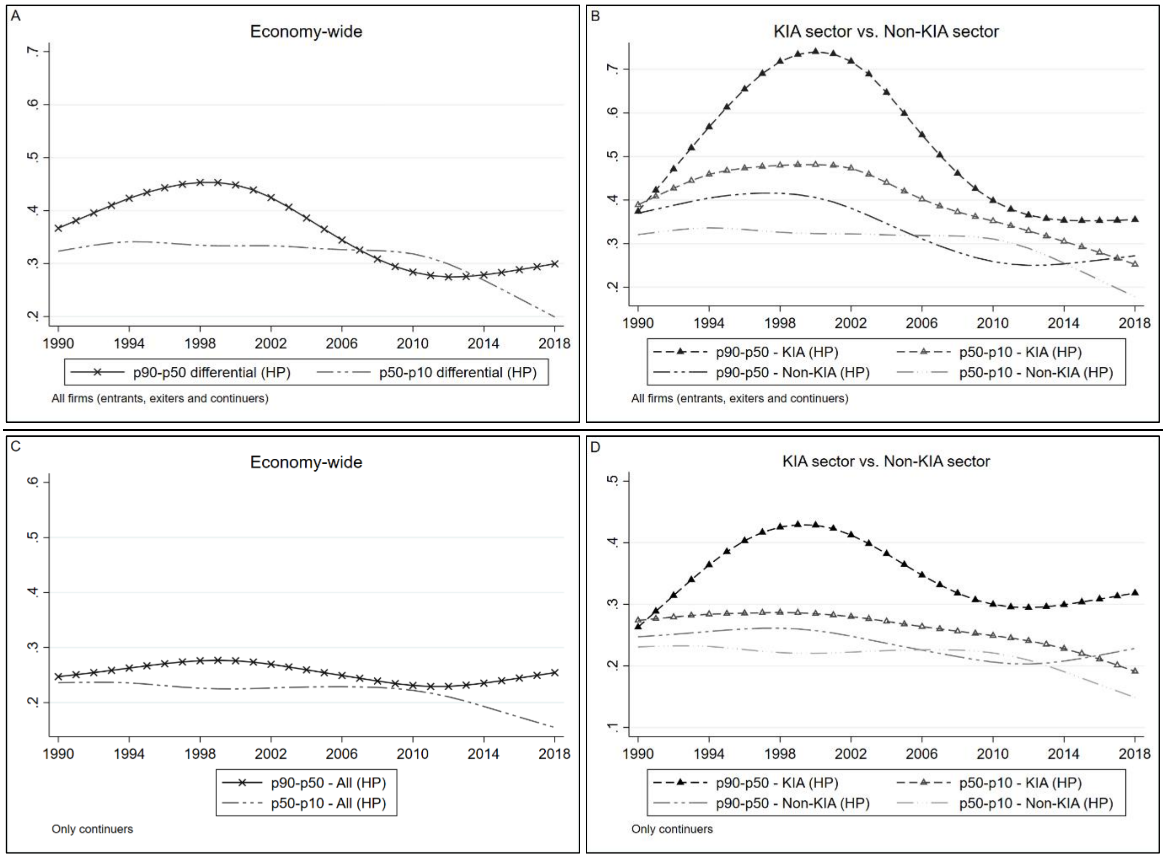


Note: The figure shows the employment-weighted box-and-whisker plot for continuing firms by age category for the periods 1991-2000, 2001-2010, 2011-2018. Young firms are less than 5 years old.

To further characterise the distribution skewness, Figure 5.12 shows the evolution of the differentials 90-50 and 50-10 for all and continuing firms. First, note that, unlike what happened with the dispersion, the presence of new and exiting companies does influence the skewness pattern. The differentials 90-50 and 50-10 of all firms (in panels A and B) exhibit more pronounced changes than continuing firms (in panels C and D). Second, estimates indicate that positive skewness across the economy increased until the late 1990s, declining after that and all along the first decade of the new century. However, the distribution is again more right-skewed after 2010. The gap between the 90-50 and 50-10 differentials of continuing firms is about five p.p. in 2000, 1 p.p. in 2010, and 10 p.p. in 2018. Here, it is crucial to emphasise that, while the distance between the 90th and the 50th percentile again adopts an upward trend from 2010, the narrowing of the 50-10 differential explains most of the positive-skewness increase. Thus, the skewness follows the dispersion pattern between 1986 and 2010.[57] Yet, the dispersion continues to fall from this point on while the skewness increases. Moreover, since the median remained around zero across the analysed interval (see Figure 5.11), laggard firms appear to have improved their performance over the last decade.

[57] This growth rate dynamic is different from that reported by Decker et al. (2016) for the US, where dispersion and skewness evolved in opposite directions in the pre-2000 era (i.e. descending in the former and ascending in the latter).

Figure 5.12 The skewness of the employment-weighted growth rate distribution, 1990-2018

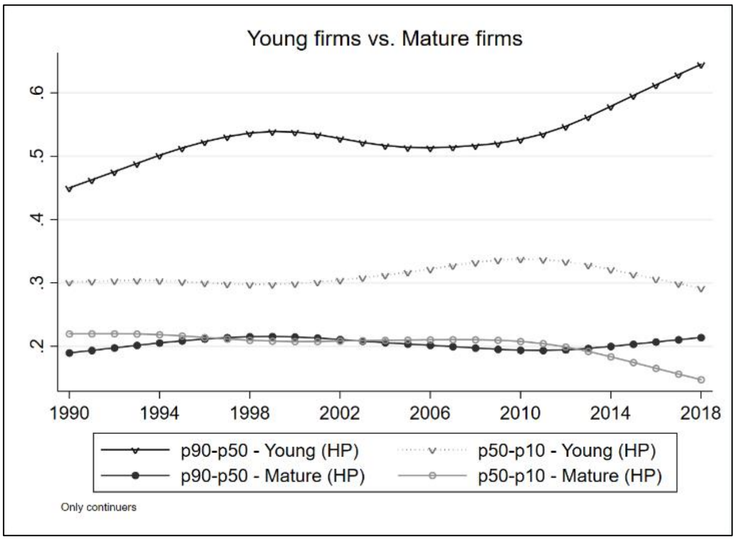


Note: The 90-50 and 50-10 differentials denote the distances between the 90th and 50th percentiles and the 50th and 10th percentiles, respectively, of the employment-weighted distribution of employment growth rates for all (upper panels) and continuing (lower panels) firms. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure 5.12 also shows the evolution of the 90-50 and 50-10 differentials for the KIA and Non-KIA sectors. Five findings stand out: *i)* the growth rate distribution of the KIA sector is more right-skewed than that of the Non-KIA sector; *ii)* the increase in positive skewness, observed until the late 20th century throughout the economy, would also be explained by the KIA sector's dynamics (in this sector, the structural gap between the 90-50 differential and the 50-10 differential of continuing firms increased from -1 p.p. to 14 p.p. between 1986 and 2000); *iii)* in the KIA and Non-KIA sectors, positive skewness decreased between 2000 and 2010; *iv)* the 90-50 (50-10) differential is widened (narrowed) during the 2010-2018 interval in both sectors. However, the higher positive skewness is mainly explained by a shorter distance between the median and the 10th percentile; and *v)* there has been a marked fall of the 90-50 differential in the knowledge-intensive sector since 2000, suggesting a slower growth of the fast-growing firms.

Nevertheless, as seen above, young firms appear to have followed a growth dynamic that is not entirely in line with what has happened either at the sectoral level or across the economy, especially over the last decade. *First*, as shown in Figure 5.13, the positive skewness widens in both categories during the 1990s, although this enlargement is significantly higher in young companies. This result confirms that infant firms played a key role in the strong job creation observed in the Portuguese economy at the end of the 20th century. *Second*, distributions of young and mature firms exhibited less positive skewness during 2000-2010, caused by a narrowing of the 90-50 differential and a widening of the 50-10 differential. *Third*, in both cases, positive skewness increases from 2010 on. However, in mature firms, this increase is explained by a narrowing of the 50-10 differential. Instead, the widening of the 90-50 differential accounts for the larger positive skewness exhibited by the distribution of young companies since 2010, in line with what the boxplot showed. Accordingly, young firms located in the distribution's right tail show a significantly higher performance during the last decade. *Finally*, skewness and dispersion have a similar pattern in the case of young firms, while for mature firms, the pattern after 2010 is distinct, with dispersion falling and skewness increasing.

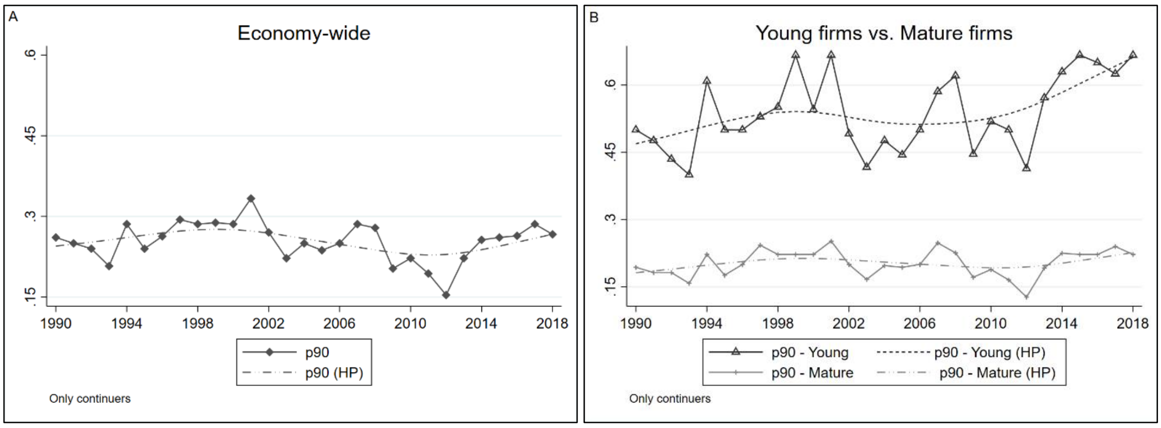
Figure 5.13 The skewness of the employment-weighted growth rate distribution by age, 1990-2018



Note: The 90-50 and 50-10 differentials denote the distances between the 90th and 50th percentiles and the 50th and 10th percentiles, respectively, of the employment-weighted distribution of employment growth rates for continuing firms by age category. Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

Figure 5.14 presents the evolution of high-growth firms (HGF). On the one hand, following skewness patterns, we observe that all HGF exhibited (even) higher rates during the 1990s, followed by a decline since 2000 and a recovery after 2010. On the other, confirming previous expectations, estimates indicate that young firms in the distribution's 90th percentile have shown increasingly higher growth rates. Using secular trend estimates, the 90th percentile growth rate of the young firms' distribution increased from 47% in 1990 to 54% in 2000, finally reaching 66% in 2018, an increase of 19 p.p. during 1990-2018. In contrast, the growth of mature firms at the 90th percentile of the distribution, although evincing a slight rise in the late 1990s and 2010s, has remained relatively constant. Clearly, mature HGF grow at a slower rate than young HGF.[58]

Figure 5.14 The evolution of high-growth firms by age category, 1990-2018



Note: The typical performance of a high-growth firm (HGF) is observed by estimating the 90th percentile growth rate. The 90th percentile is based on the employment-weighted distribution of employment growth rates for continuing firms, across the economy (left panel) and by age category (right panel). Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

In the intersectoral analysis shown in Figure 5.15, we observed, however, that the new century's higher performance of young HGF is driven by those in the non-KIA sector, particularly from 2010. Young HGF in the KIA sector exhibited increased performance during the 1990s but a declining growth pattern since 2000. This fact is somewhat surprising because, in the sector called to be more dynamic, the growth of young companies has been weakened and, therefore, their ability to compete for industrial leadership.

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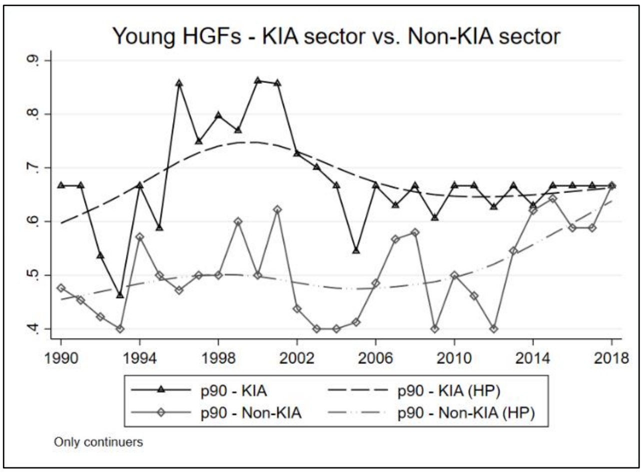
[58] Figure A.9 in the Appendix section shows HGF trends for all enterprises (i.e., including entering and exiting firms), and the trends generally hold.

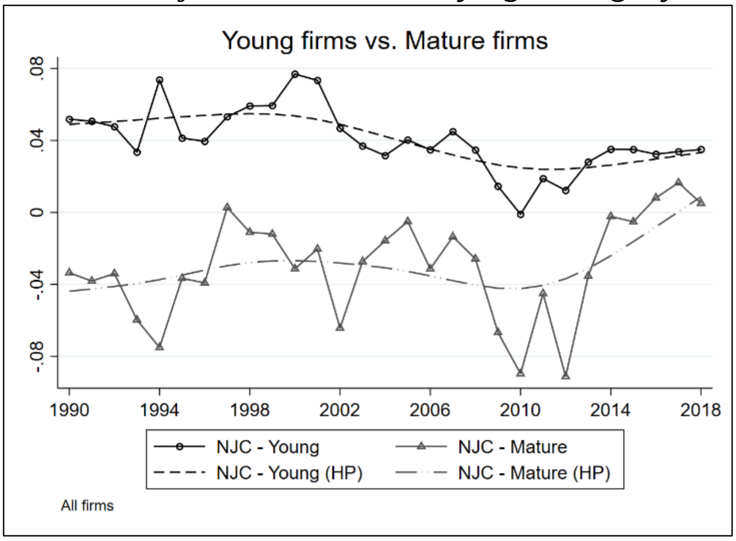
Figure 5.15 The evolution of high-growth young firms by sector, 1990-2018



Note: The typical performance of a high-growth firm (HGF) is observed by estimating the 90th percentile growth rate. The 90th percentile is based on the employment-weighted distribution of employment growth rates for continuing firms, across the economy (left panel) and by age category (right panel). Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

On the other hand, the overall improved performance of young HGF appears not to have compensated for the lower entry rate and higher early mortality hazard. As shown above, the employment share of young firms has fallen steadily from 1990 to 2018. In addition, as we observe in Figure 5.16, the contribution of young firms (including newly born enterprises) to net job creation has been reduced during the new century. In fact, while these companies still contribute most to net job creation, the contribution of mature firms has shown the most pronounced upward trend since 2010. The growing contribution of mature firms to net job creation suggests, in turn, that the less slow growth of laggards had a considerable effect on aggregate performance.

Figure 5.16 The net job creation rate by age category, 1990-2018



Note: The net job creation rate is computed as the employment-weighted average of the employment-growth rates of all firms (i.e. entering, continuing, and exiting firms), by age category. Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100.

To sum up, the observed trends indicate a structural change in business dynamism since 2000. The pre-2000 period was characterised by intense creative destruction, mainly driven by expanding knowledge-intensive activities (KIA). Job reallocation increased while newly-born and young firms played a leading role in net job creation. However, from the beginning of the new century, the entry of new competitors and their share in net job creation fell significantly. Furthermore, the job reallocation rate was markedly reduced, while growth rates were clustered around a zero median. This pattern is common across all industries. In addition, although young companies showed increasingly higher growth rates during 1990-2018 (especially those in the 90th percentile of the distribution), the risk of early mortality increased. As a result, new and young firms reduced their share in net job creation and aggregate employment. These findings suggest that the barriers to mobility worsened, undermining especially the entry and growth of transformative entrepreneurship that would otherwise have been more disruptive to the industrial order.

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6 The paradox of Schumpeterian competition: Competitive regime and productivity growth over 1990-2018

6.1 Methodology

6.1.1 Industrial structure and market contestability indices

There are several methodologies to measure the product market's competitive level. All of them, however, rest on different theoretical assumptions. Traditional indicators assess the extent to which markets are sufficiently close to perfect competition (generally analysing concentration levels, profit rates and price-cost margins). As is well known, this type of competition assumes an exogenous technology among producers and predicts convergence towards an optimal size. However, as observed in chapters 2 and 3, one of the main results in the empirical literature is the high and persistent productivity and size heterogeneity, even at the highest industrial disaggregation level (Dosi & Nelson, 2010; Syverson, 2011).

Productive heterogeneity may result from economies of scale and impaired mobility of inputs (including knowledge), as well as idiosyncratic business behaviours in terms of management practices, the propensity to innovate and take risks, and the division of labour, for example (Dosi & Nelson, 2010; Syverson, 2011). No matter the underlying causes, it seems clear that heterogeneous efficiencies must yield heterogeneous returns. Therefore, although helpful, the traditional approach provides an incomplete view of the competitive regime. If a well-functioning market rewards the most innovative or efficient units with a higher market share or profit margin—to recover fixed or sunk costs—a high concentration, or more significant and persistent markups, does not *necessarily* indicate low competitiveness.

In line with recent empirical developments, the benchmark for evaluating the proper functioning of markets appears to be creative destruction rather than perfect competition. Consequently, any margin over marginal cost (the neoclassical view) or unit variable costs (Kaleckian-Post Keynesian view) does not inevitably entail market power. Furthermore, concentration or profitability are valuable measures for assessing creative destruction as long as they are analysed in comparison with their expected determinants, namely, productive investment, technological efficiency, or innovation. In this regard, since it is very complex (if not problematic) to determine how 'fair' a market share or profitability should be to compensate for innovative efforts, what should matter is the dynamic and joint evolution of these indicators and not so much their values *per se*. For instance, creative destruction seems incompatible with the dynamics of an industry simultaneously exhibiting increasing concentration, slowing job creation, and stagnant productivity.

This thesis employs the degree of industrial concentration as a preliminary competitive regime measure. In particular, I estimate the C5 and C20 concentration indices, the proportion of sales in the industry's 5 and 20 largest firms (at the 2-digit level), respectively. Following Autor et al. (2017) and Grullon et al. (2019), the indicator is estimated for each industry, and the weighted average across industries is then computed (by major sector or the entire economy). The weighting factor is the number of firms.

Meanwhile, market power measures also have different meanings. For example, in a market with heterogeneous costs operating as a *tacit cartel*, the leader is expected to set a price that followers then take on by adjusting the unit profit margin. We can assume that only leading firms have market power in this setting. Hence, the most helpful parameter is the elasticity of demand individually faced by firms. Unfortunately, multisector databases with information on output demand are very rare.

One measure of market power that recently has become popular is De Loecker et al.'s (2020) producer approach. After a cost minimisation process of a typical company with Cobb-Douglas technology, De Loecker et al. (2020) derive the markup function $\mu_{i,t}$, defined as the output elasticity of variable inputs $\theta_{i,t}^{v}$ multiplied by the ratio between revenues $P_{i,t}Q_{it}$ and total variable costs $P_{i,t}^{V}V_{i,t}$, including the labour input and intermediates (i.e., $\mu_{i,t} = \theta_{i,t}^{v}\frac{P_{i,t}Q_{it}}{P_{i,t}^{V}V_{i,t}}$). The output elasticity can be estimated, while revenues and costs are directly observable.

Assuming that the Cobb-Douglas function does indeed represent the technology of a typical firm, I argue that the markup function has a critical flaw arising from modelling the wage rate (included in $P_{i,t}^{V}$) as an exogenous parameter. As recent empirical studies suggest, employers have a non-negligible monopsonistic power in wage determination, especially in the case of routine or low-skilled tasks (Card et al., 2018; Manning, 2011). As a result, this measure appears to be more of a unit profit rate than an indicator of the magnitude of monopoly power since it is unable to separate the product market's markup from the labour market's markup. In any event, given data limitations, we cannot calculate any profit rate measure for the entire analysis period, as data is only available from 2004 on.

On the other hand, if the benchmark is creative destruction, dynamic indicators are likely to provide a better insight into the degree of market contestability. Within this group of measures, we have, for example, the entry rate, the reallocation rate (i.e., the sum of the creation and destruction rates), the industrial turbulence (i.e., the sum of the entry and exit rates), the market share instability index, and the industrial leadership turnover. Chapter 5 presented many industrial dynamics statistics based on employment. This chapter further explores the evolution of the Hymer-Pashingian Instability Index and the industrial leadership persistence rate.

The instability index gives the sum of changes in market shares over two periods as follows:

$$\mathrm{I}_{\mathrm{j,t}} = \sum_{\mathrm{i}\in\mathrm{j}} \left| \mathrm{s}_{\mathrm{i,t}} - \mathrm{s}_{\mathrm{i,t-1}} \right|, \tag{6.1}$$

where $s_{i,t}$ is the market share of *continuing* firm i in the total sales of industry j. As Mazzucato and Tancioni (2005) point out, this measure attempts to capture changes in the firms' relative position. In other words, it accounts for the inter-firm competitive battle regardless of the industry concentration level. Thus, a highly concentrated industry with a low turbulence index suggests collusion, while the same concentration index, accompanied by high instability, indicates a high degree of competition (Carreira, 2006). Mazzucato and Tancioni (2005) argue that this index is suitable for capturing periods of intense creative destruction where innovations shake up the established industrial order.

The industrial leadership turnover measure relies on one of the most critical assumptions of creative destruction: the limited temporality of dominant positions. Hence, the lower (higher) the leadership turnover (persistence), the more likely markets have fallen into inertia, weak competitive selection, and increased accumulation of what can be called 'non-Schumpeterian rents'. This thesis uses the industrial leadership persistence rate, defined as the ratio between the number of market share leaders in t (i.e., the 5 or 20 companies with the largest market shares) that remain in leadership in $t+\tau$ and the total number of leaders in t, with $\tau = 1, 3$. As in the case of concentration ratios, instability and persistence indicators are estimated for each industry, and the weighted average across industries is subsequently calculated. The weighting factor is the number of firms in each sector.

Finally, to evaluate whether the industrial leadership persistence and concentration trends mirror the dynamics of efficiency and innovation, I assess the evolution of the mean relative productivity *level* $\overline{A^r_{i,j,t}}$ and the mean relative productivity *growth* $\overline{\Delta A^r_{i,j,t}}$ of industry leaders and followers (i.e., all the other firms), as well as the technological and innovation gaps across the two groups, computed as follows:

$$\overline{A^r_{i,j,t}} = \sum_{i \in j} \frac{1}{n} \left(A_{i,j,t} - \overline{A_{j,t}} \right), \ \forall \, i \in \{l, f\}, \tag{6.2}$$

$$\overline{\Delta A^r_{i,j,t}} = \sum_{i \in j} \frac{1}{n} \left[\left(A_{i,j,t} - A_{i,j,t-1} \right) - \left(\overline{A_{j,t}} - \overline{A_{j,t-1}} \right) \right], \forall \, i \in \{l, f\}, \tag{6.3}$$

where subscripts i and j denote (continuing) firm and industry (2-digit level), respectively, while l and f indicate leaders and followers. Note that the chosen statistical procedure allows for an in-depth exploration of the performance of the 5 and 20 industrial leaders over the last three decades, given the evolution of their market share and persistence ability compared with their productivity and innovation levels.

To separate the time series into trend and cyclical components, I use the Hodrick-Prescott (HP) filter (with a smoothing parameter equal to 100). I also pay special attention to intersectoral evaluations according to the knowledge intensity level (whose classification was presented in chapter 4) to map the different trajectories resulting from the emergence of the ICT technological paradigm.

It is worth noting that the estimation of these indicators suffers from one of the most common limitations when evaluating the industry's competitive level. That is, the inability to accurately define the relevant market, that is, the one that includes all producers with high cross-output demand elasticity. The difficulty relies on how industries are classified (i.e., based on production technologies instead of demand features) and the available industrial disaggregation level. This inquiry is particularly constrained by the time-consistent industry classification, which reduced the disaggregation to two digits.

In line with the trends presented in Chapter 5, I expect that stable or declining concentration, high instability, less entrenchment of leaders, and a larger (or at least constant) relative productivity and innovation gaps between leaders and followers characterised the competitive regime during the ICT technological paradigm's initial phase (that is, during the 1980s and 1990s), the opposite occurring since the beginning of the new century. As a result, I anticipate a Schumpeterian concentration during the late 20th century and a non-

Schumpeterian one from the new century onwards (i.e., a concentration not exclusively driven by innovation differentials).

6.1.2 The relationship between competition and concentration

In markets characterised by broad and persistent productivity heterogeneity, operating in a creative destruction setting, the competition degree is expected to be revealed primarily by the strength of market selection (Dosi et al., 2015). In other words, via the relationship between relative productivity growth and firm expansion, the expected critical outcome of Schumpeterian competition.

Observe that this result must be true regardless of the theoretical approach. For instance, in the endogenous growth model of Aghion et al. (2001), where a Bertrand duopoly with asymmetric costs and differentiated products describes the typical market, the firm with the lowest relative cost obtains the most considerable proportion of profits and output (see Chapter 2).[59] Similarly, all firm dynamics models predict that market shares are directly proportional to relative efficiencies (Hopenhayn, 1992; Winter et al., 2003). Hence, demand-side and supply-side market selection frictions are expected to weaken this relationship. For instance, if search and transportation costs prevent consumers from buying from high-productivity firms, cross-demand elasticities will be relatively low, and the innovation-growth relationship will be weaker. In addition, if financial constraints (or labour market frictions) hinder the growth of high-efficiency units, the innovation-growth relationship is also undermined.

To avoid the discussion on functional forms, let us use as a starting point a standard evolutionary replicator dynamic as follows:

$$\Delta \mathrm{s}_{\mathrm{i,t}} = f\left(\Delta \mathrm{A}^{\mathrm{r}}_{\mathrm{i,t}}\right)\mathrm{s}_{\mathrm{i,t-1}}, \tag{6.4}$$

where $\mathrm{s}_{\mathrm{i,t}}$ denotes the market share of firm i in period t, while $\mathrm{A}^{\mathrm{r}}_{\mathrm{i,t}}$ stands for the firm relative productivity (i.e., as a deviation from the industry mean). Following Dosi et al. (2015), I use the *change* in relative productivity between t and $t-1$ (as a proxy for innovation) as the independent variable of the function f rather than the *level* of relative productivity in t.[60]

[59] In a Cournot competition with asymmetric costs, the larger the relative cost reduction, the greater the market share growth (Carlton & Perloff, 2015).

[60] Dosi et al. (2015) reported that productivity change is a better predictor of firm growth than productivity level.

This formulation suggests that, conditional on initial size, firms with above-average increases in productivity grow faster, while the opposite occurs with less innovative companies.

Nevertheless, Bottazzi et al. (2010) and Dosi et al. (2015) found that productivity levels and changes explain a limited proportion of the firm growth variance.[61] This relatively weak explanatory power may result from the low (and supply-side) industrial disaggregation at which the regressions were produced (at the 2-digit level) and, thus, from a poorly defined market. In any event, the estimates suggest that other variables influence the market structure. This replicator dynamics formulation also seems somewhat optimistic since, other than initial size, all business growth is determined by relative efficiency or innovativeness.

The central hypothesis of this chapter holds that the level of industrial concentration negatively conditions business growth, innovation and market selection, especially when the expected return on innovation enters its declining phase. This premise agrees to some extent with one of the main predictions of the seminal model by Dasgupta and Stiglitz (1980), which claims that innovative efforts are positively correlated with the allocation of market shares when concentration is low. This hypothesis is also partially in line with the theory of Robinson (1962), who suggested that as markets become dominated by powerful, old firms, the fear of new competition decreases, and, as a result, the need to accumulate and innovate.

Nevertheless, given the form of competition (i.e., competition for the market), these presumptions appear to entail a paradoxical relationship since *competition tends to (Schumpeterian) concentration, and concentration in turn weakens competition.* This relationship, for example, may explain why industrial dynamics in the United States evolved from *good* concentration during the 1990s (with increasing productivity, falling prices, and high investment and instability of market shares) to *bad* concentration in the new century (with low productivity growth, rising prices, weak investment, and persistent market shares) (Covarrubias et al., 2020). Hence, I argue that bad concentration (i.e., non-Schumpeterian) is made possible by good concentration (i.e., Schumpeterian).

Why would market concentration weaken competition? First, as Robinson (1962) and Arrow (1962) suggested, accumulation and market dominance discourage the generation of more

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[61] In particular, Dosi et al. (2015) found that the change in productivity explains on average between 12% and 18% of the business growth variance, in the manufacturing sector (at the 2-digit level) in the US, UK, Germany, and France.

innovation. Second, it would facilitate the prevalence of what Geroski et al. (1985) defined as structural and behavioural mobility barriers. Structural barriers such as economies of scale, high cost of technology, and network externalities are expected to be more relevant as markets become more concentrated and mature, especially in high-tech industries (Mazzucato et al., 2020; Philippon, 2019; Stiglitz, 2018), as mentioned in Chapter 2. Likewise, a more significant concentration supposes an accumulation of financing in a few companies, which likely impairs the funding availability for would-be innovators (Lambert, 2019; Robinson, 1962).

On the other hand, the growing importance of behavioural barriers in more concentrated markets also rests on Arrow's replacement effect hypothesis, which claims that more extensive monopoly power entails a greater opportunity cost of continuing to innovate (or adopt new technologies) and, thus, a more entrenched conservative position (Arrow, 1962; Holmes et al., 2012). This proposition is connected with the findings by Geroski and Toker (1996) and, more recently, Stiglitz (2019), Philippon (2019), Reich (2015), Tepper and Hearn (2018), Shapiro (2019), and many others, who indicated that larger firm size (and resources) facilitates the preservation of a dominant position. In particular, it enables discouraging the entry and growth of competing firms (e.g., through advertising, use of Big Data, or limit pricing), achieving pre-emptive mergers and acquisitions, devoting plenty of resources to institutional lobbying, and obtaining financing. In addition, more concentrated markets favour the success of cartel agreements—due to lower monitoring costs (Levenstein & Suslow, 2006). In other words, excessive concentration enables market selection to be circumvented while lowering the incentives for leaders to continue innovating. Finally, if the return to innovation is low (due to exhaustion of inventiveness, for example), dominant companies are likely to have more incentives to adopt anti-competitive practices.

In this context, I propose the following modified version of the evolutionary replicator dynamics:

$$\Delta \mathrm{s}_{\mathrm{i,t}} = f\left(\Delta \mathrm{A}^{\mathrm{r}}_{\mathrm{i,j,t}}, \mathrm{C}^{\mathrm{k}}_{\mathrm{j,t}}, \mathbf{X}_{\mathbf{i,j,t}}\right)\mathrm{s}_{\mathrm{i,j,t-1}}, \tag{6.5}$$

which means that, conditional on the initial size, market share growth is a function of the relative productivity growth of company *i* in industry *j*; the concentration ratio C^k in industry *j*; and firm and industrial level variables contained in **X,** such that business age or cash flow in the case of the firm, or creditor forbearance in the sectorial case, inter alia.[62] In addition, f is characterised by the following properties:

$$\frac{\partial f\left(\Delta \mathrm{A}_{\mathrm{i,j,t}}^{\mathrm{r}}, \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}}, \mathbf{X}\right)}{\partial \Delta \mathrm{A}_{\mathrm{i,j,t}}^{\mathrm{r}}} > 0, \tag{6.6}$$

$$\frac{\partial f\left(\Delta \mathrm{A}_{\mathrm{i,j,t}}^{\mathrm{r}}, \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}}, \mathbf{X}\right)}{\partial \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}}} < 0, \tag{6.7}$$

and, particularly:

$$\frac{\partial^2 f\left(\Delta \mathrm{A}_{\mathrm{i,j,t}}^{\mathrm{r}}, \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}}, \mathbf{X}\right)}{\partial \Delta \mathrm{A}_{\mathrm{i,j,t}}^{\mathrm{r}} \partial \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}}} < 0, \tag{6.8}$$

The hypothesis is, therefore, that *the innovation-market share growth relationship is weaker when industry concentration is greater.*

To analyse the relationship between (Schumpeterian) competition and concentration, I first implement the following industry-level OLS regressions (with industry-clustered standard errors):

$$\mathrm{PR}_{\mathrm{j,t}}^{\mathrm{k}} = \varphi_0 + \varphi_1 \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}} + \mathbf{Z_{j,t}}'\mathbf{\Omega} + \eta_{\mathrm{j,t}}, \tag{6.9}$$

$$\mathrm{I}_{\mathrm{j,t}} = \theta_0 + \theta_1 \mathrm{C}_{\mathrm{j,t}}^{\mathrm{k}} + \mathbf{Z_{j,t}}'\mathbf{\Phi} + \zeta_{\mathrm{j,t}}, \tag{6.10}$$

$$\mathrm{I}_{\mathrm{j,t}} = \sigma_0 + \sigma_1 \mathrm{PR}_{\mathrm{j,t}} + \mathbf{Z_{j,t}}'\mathbf{\Psi} + \xi_{\mathrm{j,t}}, \tag{6.11}$$

$$\overline{\Delta \mathrm{A}_{\mathrm{l,J,t}}^{\mathrm{r}}}^{\mathrm{k}} = \lambda_0 + \lambda_1 \mathrm{I}_{\mathrm{j,t}} + \mathbf{Z_{j,t}}'\mathbf{\Upsilon} + \upsilon_{\mathrm{j,t}}, \tag{6.12}$$

where $PR_{j,t}^{k}$ denotes the leadership persistence rate, $C_{j,t}^{k}$ the market share, and $\overline{\Delta A_{l,J,t}^{r}}$ the mean relative productivity growth of the k industrial leaders (with k ∈ $\{5,20\}$). $I_{j,t}$ stands for the market share instability index, computed as shown in (6.1). The matrix $\boldsymbol{Z_{j,t}}$ contains two control variables: a dummy for knowledge-intensive activities and a business cycle measure (calculated as the weighted average of the cyclical component of net job creation by region, with the weighting factor being the number of firms). I expect higher concentration to be negatively (positively) correlated with market share instability (persistence of industrial leadership). I also anticipate a negative sign for σ_1, meaning that the higher the leaders' entrenchment, the lower the industrial instability of market shares.

[62] The effect of credit forbearance on business growth and exit selection is analysed in the next chapter.

Finally, I expect leaders to have fewer incentives to innovate in less competitive environments (i.e., with lower instability).

A crucial empirical strategy intended to examine the paradox between competition and concentration is given by an econometric model based on the modified replicator dynamics presented in (5), as follows:

$$\Delta s_{i,j,t} = c + \beta \Delta A^{r}_{i,j,t} + \gamma C^{k}_{j,t} + \alpha\left(\Delta A^{r}_{i,j,t} * C^{k}_{j,t}\right) + \lambda s_{i,j,t-1} + \mathbf{X}'_{i,j,t}\mathbf{\Theta_D} + \mu_i + \varepsilon_{i,j,t}, \quad (6.13)$$

where subscripts *i* and *j* denote (continuing) firm and industry (2-digit level), respectively. μ_i refers to the time-invariant idiosyncratic firm characteristics and is assumed to be correlated with the covariance matrix (so that a panel fixed-effects regression is applied). The dependent variable $\Delta s_{i,j,t}$ denotes market share growth, measured as a log difference. The variable $\Delta A^{r}_{i,j,t}$ stands for the relative productivity growth computed as the productivity growth of the firm *i* minus the average productivity growth of industry *j* (i.e., as a deviation from industry mean productivity growth). Firm and industry productivity growth is computed in log differences. The selected efficiency measure is given by RLP, that is, revenue labour productivity, available for the entire sample period. I also use the TFP measure for robustness tests, using data only from the 2004-2018 interval. $C^{k}_{j,t}$ denotes the industrial concentration ratio, with $k=5$ (or *20*).

In addition to the log initial market share $s_{i,j,t-1}$, the matrix of control variables contains a dummy variable for young firms (less than five years old), the business cycle measure, and location, industry and year dummies. To avoid contamination from the business cycle effect on selection (such as the cleansing effect of recessions), I also include an interaction between productivity and the cyclical variable in $\boldsymbol{X}$. Moreover, I perform this model separately for each sector type (KIA vs Non-KIA) and each firm age category (young vs mature). The age is constructed based on the entry year, and young firms are less than five years old.

Consistent with equations (6.6) and (6.7), I expect a positive value for β and a negative one for γ. In this case, companies with above-average productivity growth are expected to experience higher market share growth, and companies in more concentrated markets are expected to grow more slowly, respectively. On the other hand, according to the cross derivative in equation (6.8), I anticipate a negative sign for α, implying that the innovation-market share growth relationship is likely to weaken with industrial concentration.

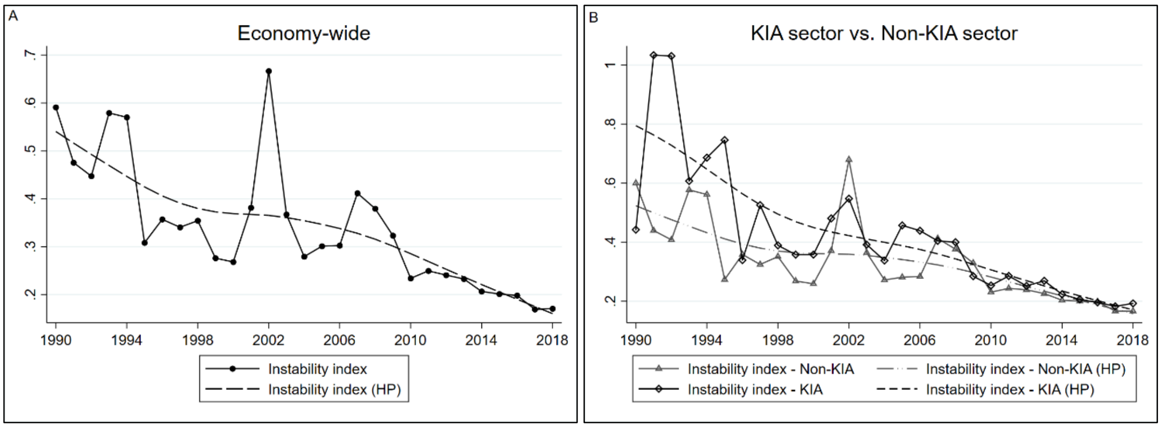
All continuous variables were winsorised at the 1st and 99th percentiles, while the regressions use the estimated inverse propensity scores as sampling weights.

6.2 Estimation results

6.2.1 From Schumpeterian to non-Schumpeterian concentration

Let us begin the competitive regime analysis by looking at industrial instability patterns. For this purpose, Figure 6.1 presents the evolution of the instability index in the average Portuguese industry during the 1990-2018 interval. High instability is a symptom of vigorous competition, generally associated with periods of intense creative destruction. However, the estimates show a persistent trend towards market stabilisation over the last thirty years (see panel A). Moreover, although the average industry exhibited greater instability during the 1990s, the figure shows a downward pattern throughout the sample window, whose index fell from 54.1% in 1990 to just 16% in 2018.[63] Therefore, the preliminary evidence suggests a secular weakening of the competitive regime.[64]

Figure 6.1 The average market share instability index across two-digit industries, 1990-2018



Note: The 'market share instability index' measures the summation of the absolute change in market shares in each year. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries by major sector. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

[63] Only the structural trend values (HP) are used in this section.

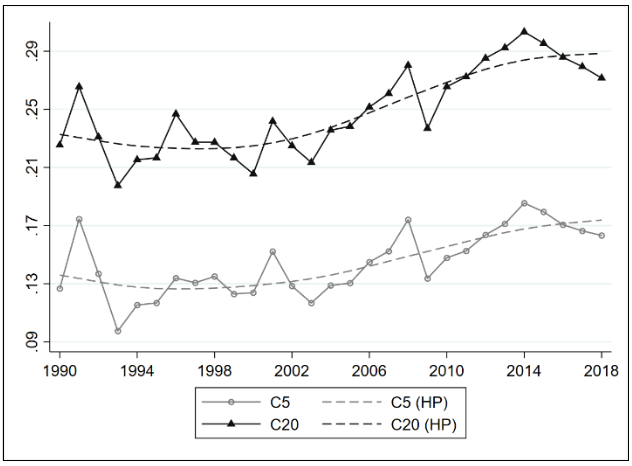
[64] Figure B.1 in the Appendix B shows the evolution of the instability index by sector of economic specialization. Despite intersectoral differences, the downward trends are confirmed throughout.

In panel B of Figure 6.1, we observe the instability pattern disaggregated by the knowledge intensity of the sector. The knowledge-intensive activities (KIA) sector is more competitive (i.e., with a higher instability) than the Non-KIA sector. This fact is particularly evident during the 1990s, highlighting again the crucial contribution of industries directly driven by the ICT technological paradigm in impelling creative destruction. Both sectors, however, exhibit waning secular instability, with the KIA sector declining more sharply. In particular, between 1990 and 2018, the instability index decreased from 52.36% (79.5%) to 15.81% (17.1%) in the Non-KIA (KIA) sector. Here it is worth noting that the selected measure focuses on the dynamics of continuing firms. Hence, it excludes the dynamism brought by entering and exiting companies, which, as observed in chapter 5, played a critical role during the late 20th century. The main conclusion is, in any case, that industrial instability—and, therefore, market contestability—has markedly slowed down in the last thirty years.

In a Schumpeterian competition, concentration and industrial leadership trends are expected to portray the patterns of productivity and innovation. Next, I focus on the behaviour of the dominant firms by inspecting their market share and leadership persistence rate compared to their efficiency and innovation levels.

The sales concentration in the 5 and 20 largest companies in a typical industry is presented in Figure 6.3. As anticipated, a slightly declining concentration characterised the market structure of the 1990s. During that interval, the concentration in the top 5 (20) industry leaders remained around 13% (23%). The new century, however, seems to have a structural break in industry dynamics. In this case, we also observe a growing trend of sales accumulation in the industrial leaders from 2000 on. Specifically, the concentration ratio C5 (C20) increased from 12.9% (22.5%) in 2000 to roughly 17% (29%) in 2018, an increase of 4.1 p.p. and 6.5 p.p., respectively.

Figure 6.2 The average sales concentration across two-digit industries, 1990-2018

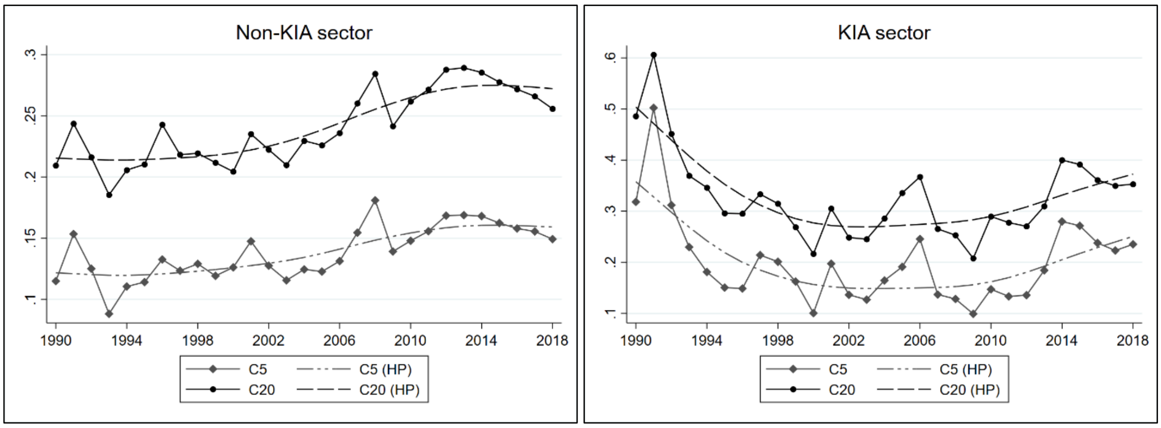


Note: The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in the industry. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is calculated the weighted average across all industries. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

Figure 6.4 shows concentration trends differentiated by sectorial knowledge intensity. First, we observe that concentration stayed quite stable in the Non-KIA sector during the 90s. Here, the accumulation of sales in the 5 and the 20 dominant companies remained at around 12% and 21.5%, respectively. But, confirming previous expectations, the industry leaders in the KIA sector actually saw their market share declining significantly during the late 20th century, where the C5 (C20) ratio fell from 35.8% (50.4%) in 1990 to 15.7% (27.7%) in 2000. Nonetheless, market concentration has risen steadily in both sectors during the new century. From 2000 to 2018, the C5 and C20 ratios increased by 3 p.p. and 5 p.p. in the Non-KIA sector, and 9.4 p.p. and 10 p.p. in the KIA sector, respectively.[65]

[65] Figure B.2 in the Appendix B shows the evolution of the concentration ratios by sector of economic specialization. With the exception of the accommodation and food service sector, and the recreational and sporting activities subsector, all sectors exhibit a significant increase in concentration in the 5 and 20 dominant firms since 2000.

Figure 6.3 The average sales concentration across two-digit industries by sector, 1990-2018

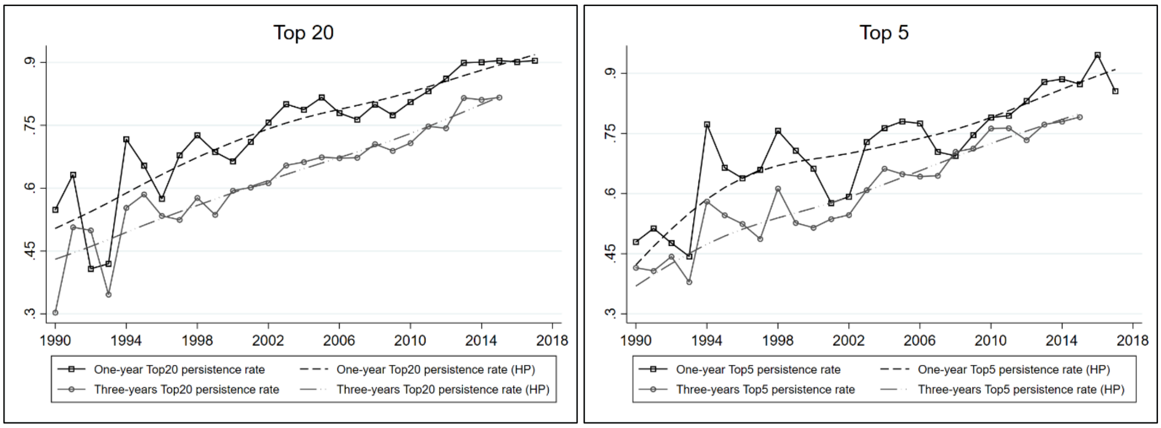


Note: The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in the industry. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is calculated the weighted average across all industries by major sector. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis.

So far, the evidence suggests that the competitive regime has weakened, even in the industries called to be more dynamic, namely after 2000. One of the critical indicators to check market contestability is the turnover in industry leadership. A Schumpeterian competition supposes an ongoing battle to become the market leader. That battle should enhance productivity growth since industrial dominance is only sustainable via cost (quality-adjusted) advantage.

Nevertheless, the evidence presented in Figure 6.5 shows that the market share leaders strengthened their entrenchment over time. Since the average value for a binary variable is the proportion of times that the variable is equal to one or the likelihood that $x_i = 1$ (remaining as a leader, in this case), the persistence rate accounts for a raw probability. Hence, the results indicate that the likelihood of staying in the Top 5 in the next year (three years) increased from 42% (37%) in 1990 to 69% (56%) in 2000 and, finally, to 91% (80%) in 2017 (2015). That is, a rise of approximately 49 p.p. between 1990 and 2017 in the case of one-year leadership persistence. For the top 20 industry leaders, the one-year persistence rate increased by 42 p.p. (from 50% to 92% in 1990-2017), while the three-year persistence rate increased by 39 p.p. (from 43% to 82% in 1990-2015).

Figure 6.4 The average leadership persistence rate across two-digit industries, 1990-2017

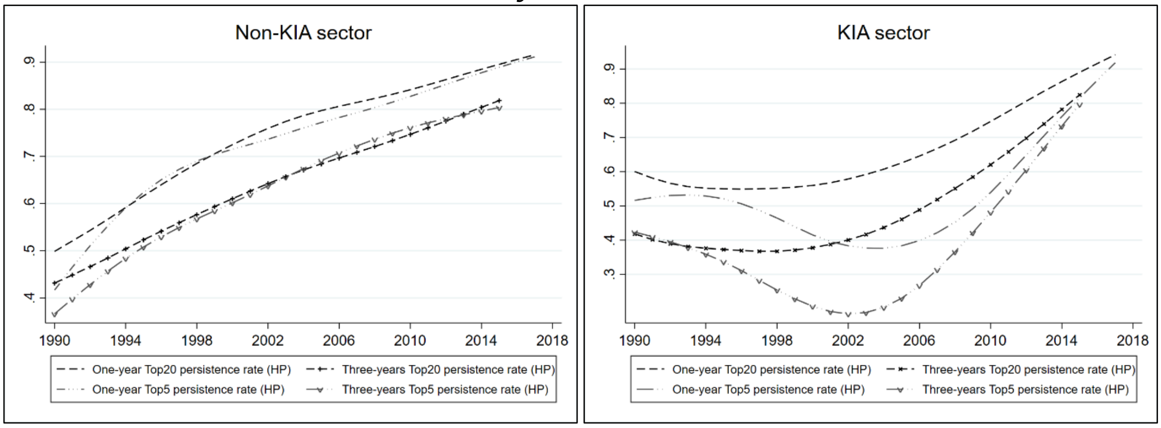


Note: The leadership persistence rate is defined as the ratio of market share leaders in t remaining in the leadership in $t + \tau$ to the total number of leading firms in t, with $\tau = 1, 3$. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

Looking at inter-sectoral trends, the results show, on the one hand, that the 5 and 20 leaders in the Non-KIA sector systematically reinforced their dominant position over time, with one-year (three-year) leadership persistence rates increasing by around 49 (43) p.p. and 42 (39) p.p. in 1990-2017 (1990-2015). On the other hand, in line with the instability and concentration findings, the estimations show that leadership entrenchment actually decreased in the KIA industries up to the beginning of the new century. This result is more evident in the case of the Top 5 firms, where the one-year (three-year) leadership persistence rate decreased from 52% (42%) in 1990 to 38% (18%) in 2002. That is, with a probability of only 18%, almost no KIA-dominant firm in 2002 had its leadership position assured after three years. Consequently, the evidence is such that a more intense creative destruction leads to higher market share instability, lower concentration, and a smaller probability of leadership persistence, especially in industries directly influenced by the new technological paradigm. Nevertheless, leadership entrenchment is also consolidated in the KIA sector from the new century on, where the one-year (three-year) persistence rate of the five leaders sharply increased by approximately 54 (62) p.p. between 2000 and 2017 (2015), reaching levels above 90% (80%).[66]

[66] As Figure B.3 in the Appendix shows, the greater entrenchment of dominant firms is confirmed in all sectors of economic specialization.

Figure 6.5 The average leadership persistence rate across two-digit industries by sector, 1990-2017



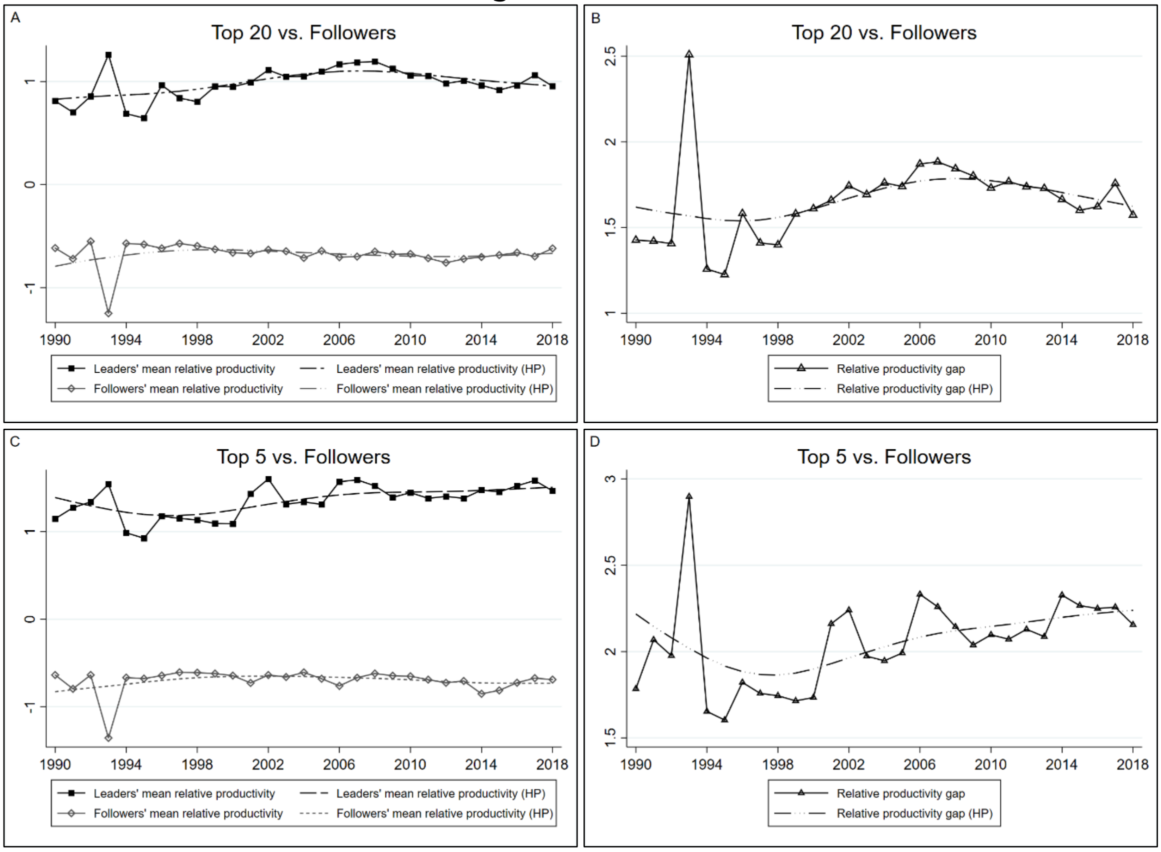
Note: The leadership persistence rate is defined as the ratio of market share leaders in t remaining in the leadership in $t + \tau$ to the total number of leading firms in t, with $\tau = 1, 3$. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries by major sector. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Finally, the crucial variables in determining the character of the change in the competitive regime are the (relative) productivity and innovation gaps between leaders and followers. After all, one could argue that industry leaders expanded their market share and persistence likelihood because they increased productivity more and faster than their followers did. In that case, we have Schumpeterian concentration proper.

Let us start with the evolution of the productivity gap. Here it is worth emphasising that the employed efficiency measures are relative to the industrial annual mean. Therefore, they reflect the extent to which leaders (followers) have outperformed (fallen behind) the average competitor. This productivity gap is a critical indicator of creative destruction since it portrays the dynamics of innovation, imitation, and selection. Leaders' innovation widens the gap, while followers' imitation closes it. In turn, the selection effect—responsible for eliminating or reducing the share of inefficient units and thus increasing the average productivity of industry and followers—also exerts pressure toward technological convergence.

Figure 6.7 accordingly shows the evolution of the average relative productivity of leaders and followers. The results indicate that the relative productivity gap significantly decreased during the 1990s. This reduction is most evident in the gap between the top 5 firms and all the other firms (panels C and D), suggesting that their immediate followers (that is, between the 6th and 20th companies) were active competitors located within a short technological distance from the top leaders.[67] Therefore, imitation and selection seem to have prevailed over leaders' innovation in the average industry during the 90s, encouraging the narrowing of the technological gap. However, dominant companies have also moved steadily away from their followers in the new century. This fact is particularly true regarding the top 5 companies, meaning that, in this case, their immediate followers (i.e., between the 6th and 20th companies) were no longer so close technologically.[68] Specifically, the relative productivity gap between the top 5 firms and their followers increased from 1.9 log points in 2000 to 2.24 in 2018. In each respective year, the leaders' relative productivity was equal to 1.25 and 1.51 log points, while that of the followers was -0.65 and -0.73. Thus, the productivity gap has widened due to lower followers' efficiency but, to a greater extent, a more significant leader's efficiency.

Figure 6.6 The average productivity gap between leaders and followers across two-digit industries, 1990-2018



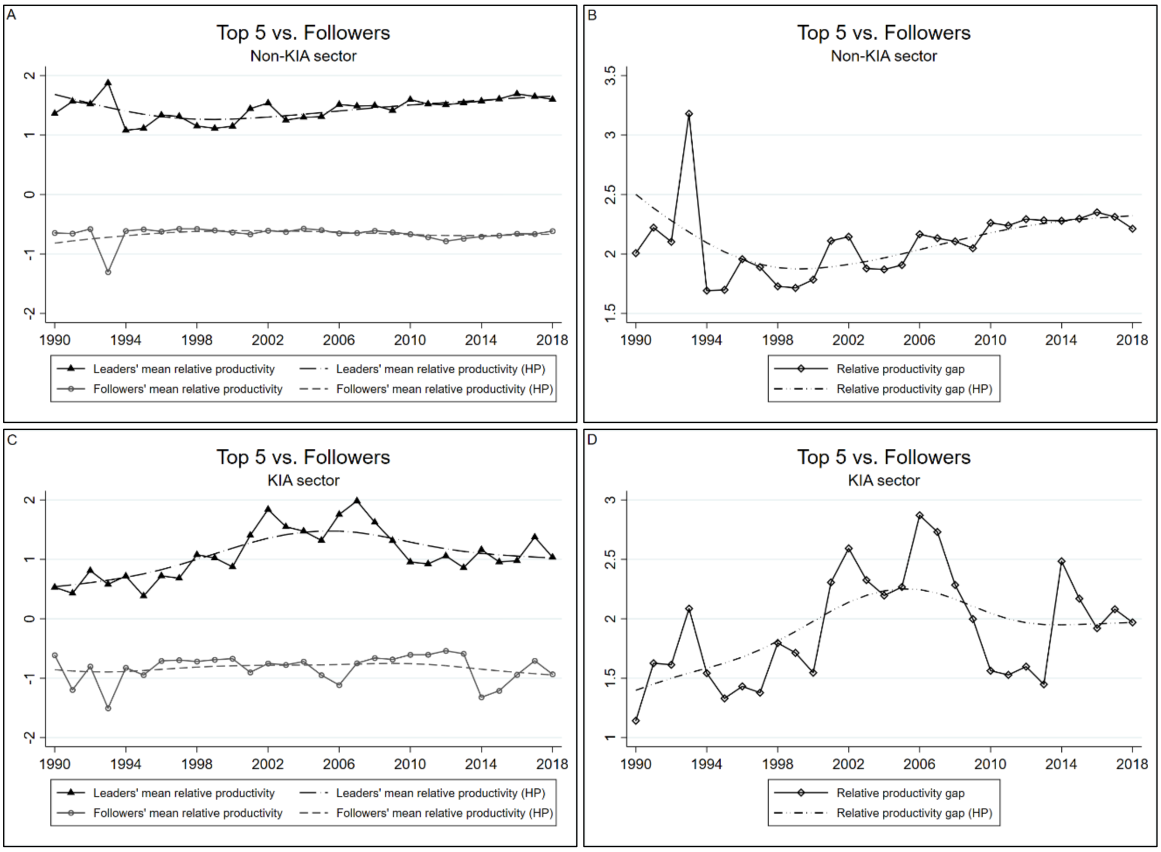
Note: The relative productivity gap corresponds to the difference between the average relative productivity of the 20 (5) market share leaders and that of the followers in a typical industry. The selected efficiency measure is Revenue Labour Productivity (RLP), calculated as sales per worker and expressed as a deviation from the industry mean. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

67 Its incorporation in the calculation raises the leaders' average (when it comes to the 20 frontier firms) or raises the followers' average (when it comes to the 5 frontiers).

68 In that case, their inclusion in the calculation decreases the average efficiency of the leaders (when it comes to the 20 frontier companies).

The analysis disaggregated by knowledge intensity shows, in Figure 6.8, that the productivity gap between leaders and followers in traditional industries (i.e., Non-KIA) exhibited a markedly different pattern from that of the KIA sector. Mirroring economy-wide trends, the technological gap in the Non-KIA sector narrowed during the 1990s and has steadily widened since 2000. Yet, the productivity gap in the KIA sector has exhibited a growing trend throughout the analysis period, particularly up to 2006. In these industries, the top 5 leaders increased technological distance from their followers during the 1990s and until 2006. From that year on, however, the leaders' relative productivity has meaningfully decreased. Meanwhile, the followers' relative productivity experienced a decline in the early 1990s, then a steady trend through 2010, and a subsequent downward pattern after that. As a result, the productivity gap has remained constant during the last decade.

Figure 6.7 The average productivity gap between leaders and followers across two-digit industries by sector, 1990-2018



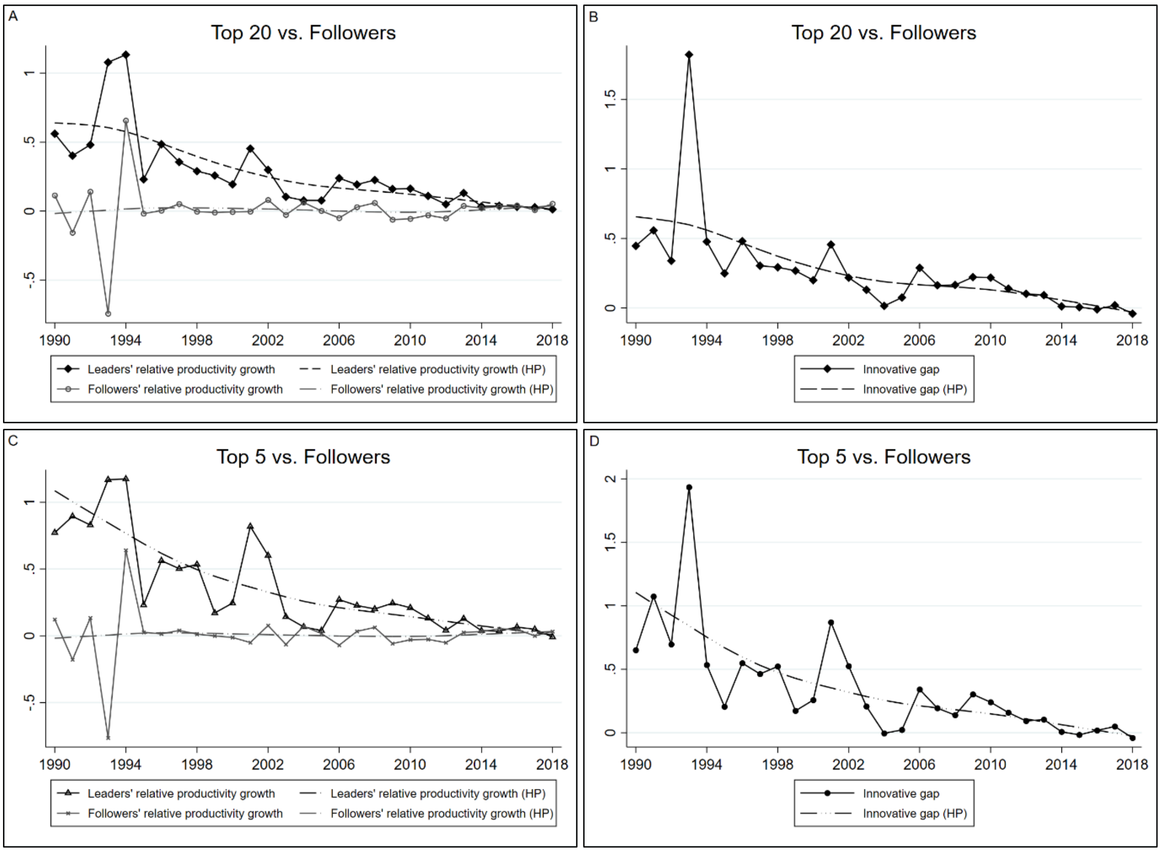
Note: The relative productivity gap corresponds to the difference between the average relative productivity of the 5 market share leaders and that of the followers in a typical industry. The selected efficiency measure is Revenue Labour Productivity (RLP), calculated as sales per worker and expressed as a deviation from the industry mean. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Other studies have also reported that dominant firms have increased the technological gap with respect to their followers in most advanced economies (Andrews et al., 2015; Autor et al., 2017). This fact has led several authors to conclude that the new century concentration only reflects a more remarkable ability of leaders to generate or adopt new technologies. Scholars like Autor et al. (2017) further claim that a "winner takes all" phenomenon occurred during this period. Consistent with the model of Aghion et al. (2001), discussed in chapter 2, in such a scenario, there is an increased cross-demand elasticity (e.g., due to lower information costs thanks to the internet) that, in a Bertrand competition with asymmetric costs, favours the most efficient producers with (almost) the entire market.

Nevertheless, if winners are taking all, and concentration is efficient, I wonder why the relative technological gap has widened instead of narrowing. In other words, with resources reallocated to more efficient uses, one would expect an increase in the average efficiency of the industry and of the followers and, therefore, a reduction in the productivity gap (as occurred in the 1990s). Second, what prevents followers from imitating and drawing closer to leaders, particularly in the context of slowing technological progress? Third, we note that the Portuguese industrial leaders' productivity stagnated after an increasing trend at the beginning of the new century. So, the issue is whether dominant companies have become more or less innovative during the last decades. Regarding the previous question, the technology gap seems to be an incomplete measure to characterise the determinants of market structure. Therefore, instead of analysing the gap in productivity *levels* between leaders and followers, it becomes critical to explore the gap in productivity *growth* between the two groups (i.e., the innovation gap).

Figure 6.9 shows the evolution of the average relative productivity growth (i.e., as a deviation from the industry average) of the leaders and their followers, and the corresponding gap between both groups. The results show that while the relative productivity growth of followers has remained stagnant (close to zero), dominant firms exhibit a secular downward trend in productivity growth over time. As a result, the innovation gap has all but closed by 2018. Since it is a relative measure, both groups are growing at the average industry rate. Specifically, the top 5 relative productivity in a typical industry grew 1.11 log points faster than their followers in 1990, 0.39 points in 2000, 0.15 points in 2010, and 0.02 points *slower* in 2018. Finally, as there has also occurred a greater accumulation of sales and entrenchment at the top of the market structure, the evidence suggests that leaders have relied less on productivity increases to expand their market share and preserve their dominant position.[69]

Figure 6.8 The average innovative gap between leaders and followers across two-digit industries, 1990-2018



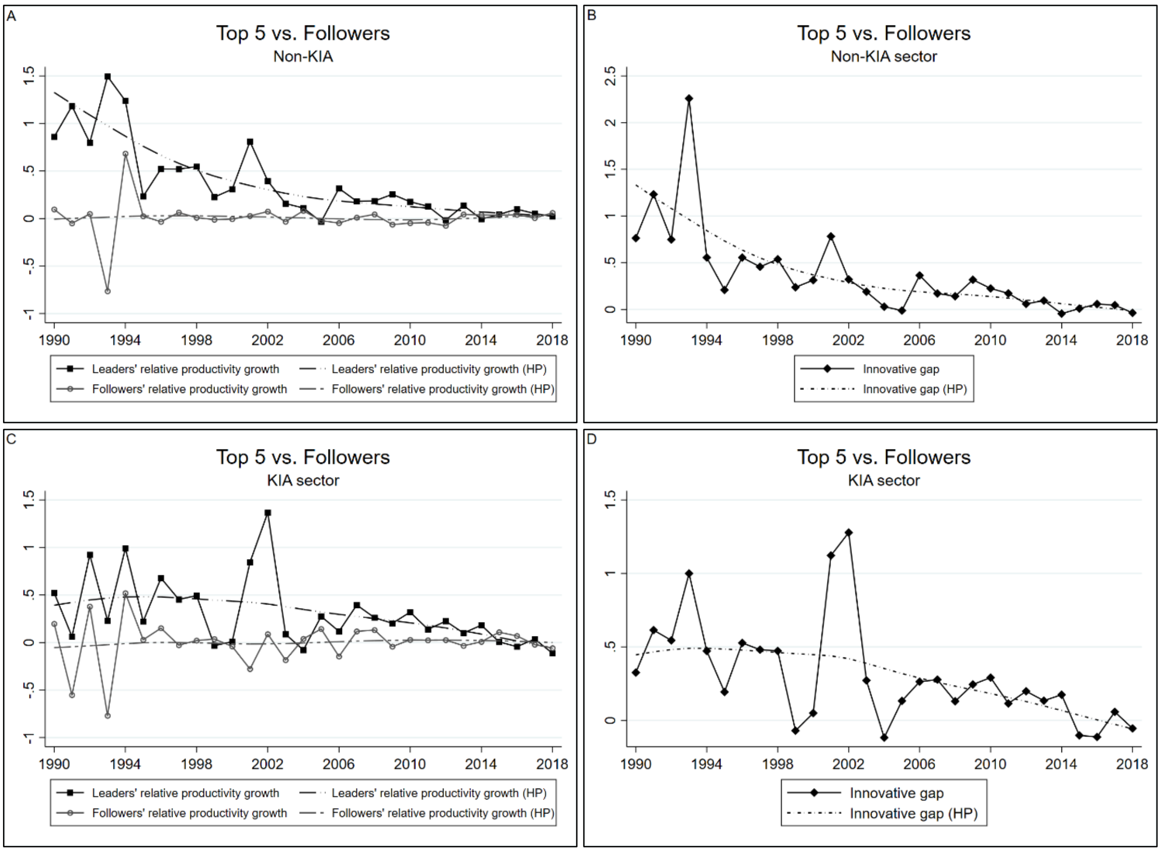
Note: The innovative gap corresponds to the difference between the average relative productivity growth of the 20 (5) market share leaders and that of the followers in a typical industry. The productivity growth is computed as log differences and as a deviation from industry average efficiency growth. The selected efficiency measure is Revenue Labour Productivity (RLP), calculated as sales per worker. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Regarding the innovation gap differentiated by the sector's knowledge intensity, we corroborate in Figure 6.10 that the leaders' relative productivity growth in the KIA and Non-KIA industries has secularly slowed down. Consequently, the innovation gap between leaders and followers vanished by 2018 in both sectors. However, it is worth noting that the innovation gap remained constant during the 90s in the KIA industries. Therefore, since the technological gap widened during this period, we can presume that, in this sector, the innovation effect dominated imitation and selection effects. Notwithstanding, the leaders'

[69] Figure B.4 in the Appendix section shows the evolution of the relative efficiency and innovation gaps using the TFP during 2005-2018. During this period, TFP-based trends mimic those based on RLP. In fact, the estimates in this case show that the followers' relative productivity growth rate would have exceeded that of the leaders.

relative productivity growth also declined after 2000, which confirms that, in both sectors, dominant companies have been able to expand their market share and increase their persistence likelihood with decreasing innovative efforts.

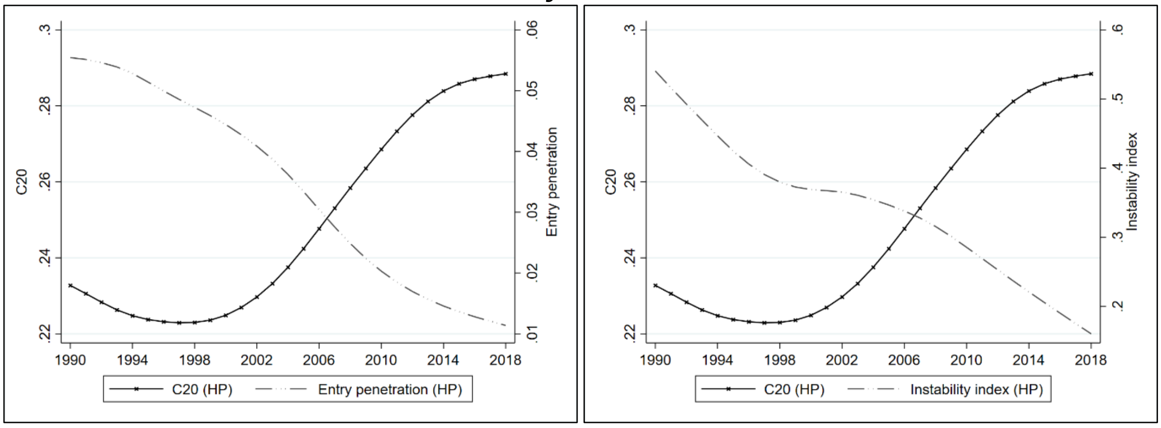
Figure 6.9 The average innovative gap between leaders and followers across two-digit industries by sector, 1990-2018



Note: The innovative gap corresponds to the difference between the average relative productivity growth of the 20 (5) market share leaders and that of the followers in a typical industry. The productivity growth is computed as log differences and as a deviation from industry average efficiency growth. The selected efficiency measure is Revenue Labour Productivity (RLP), calculated as sales per worker. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

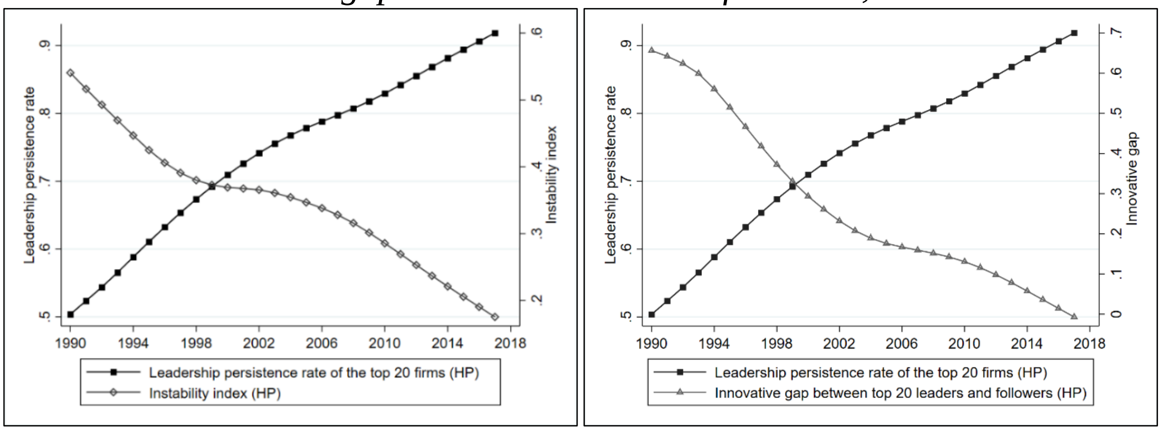
Figures 6.11 and 6.12 summarise the main findings. Figure 6.11 shows that dominant firms' market share in the average industry exhibited a convex downward trend during the 1990s and an upward pattern during the new century. As concentration increases, we also see the new firms' sales proportion and the instability of market shares fall. In turn, Figure 6.12 indicates that leadership persistence and industrial instability have exhibited an opposite trend, with leadership entrenchment rising and competitive intensity declining. In addition, as panel B of Figure 6.12 reveals, frontier firms have been able to sustain their dominant positions with diminishing innovative efforts (at present, they are growing at the same rate as the industry average). This result also implies that the most significant sales accumulation period required minor productivity increases (i.e., since 2000). At the same time, the evolution of the productivity gap suggested that followers have been increasingly unable to catch up with cutting-edge technology, which likely facilitated the entrenchment of leaders.

Figure 6.10 Sales concentration versus Entry penetration and Market share instability, 1990-2018



Note: The C20 concentration index denotes the share of sales at the 20 largest firms in the industry. The 'market share instability index' measures the summation of the absolute change in market shares in each year. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries. The weighting factor is the number of firms in each industry. The entry penetration measures the proportion of total industrial sales residing at entrant firms. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

Figure 6.11 Leadership persistence rate Versus Market share instability and the Innovative gap between leaders and followers, 1990-2017



Note: The leadership persistence rate is defined as the ratio of market share leaders in "t" remaining in the leadership in t+1 to the total number of leading firms in "t". The 'market share instability index' measures the summation of the absolute change in market shares in each year. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries by major sector. The weighting factor is the number of firms in each industry. The innovative gap corresponds to the difference between the average relative productivity growth of the 20 (5) market share leaders and that of the followers in a typical industry. Trends are computed by applying a Hodrick-Prescott filter with a smoothing parameter of 100. Y axis does not start at zero.

In short, the findings suggest that, after intense creative destruction, leaders have been able to reinforce their industrial dominance and increase their market share through determinants other than productivity growth. This pattern fully characterises a non-Schumpeterian concentration.

6.2.2 *Industry- and firm-level regressions on the relationship between innovation and market structure*

In a Schumpeterian competition, with winners expanding and losers shrinking or exiting the market, there is a tendency toward industry concentration (Nelson & Winter, 1982a). Nevertheless, this outcome is not detrimental *per se* since, in this manner, the market rewards the innovative efforts of companies that constantly push up the technological frontier. At the same time, the entry and permanent learning of new competitors are expected to prevent the entrenchment and excessive accumulation of dominant firms, so as the total exertion of their market power. This chapter tests, however, the existence of a paradoxical relationship between competition and concentration. Specifically, whether competition leads to concentration and then concentration hinders competition.

The figures in the previous section suggest that the Portuguese competitive regime has weakened, particularly during the new century, where, among other things, the degree of industrial concentration increased steadily. Accordingly, this section carries out several industry- and firm-level regressions to explore the role of market concentration in competition.

Table 6.1 shows the results of industry-level regressions that analyse the correlation between concentration, the persistence of leadership, and the instability of market shares. The leadership persistence rate is the dependent variable in specifications (1) and (2). Instead, the market share instability index is the dependent variable in specifications (3) to (6). Firstly, the findings indicate that the higher the leaders' market share, the greater their probability of persistence, shown by the positive and highly significant coefficient associated with concentration covariates. Secondly, we find that a higher level of industrial concentration is negatively correlated with industrial instability, although this relationship is only significant in the case of the C20 concentration index.

Table 6.1 OLS industry-level regressions (2-digit) on the relationships among concentration ratio, leadership persistence rate, and market share instability index

Variables	Persistence rate (20 leaders)	Persistence rate (5 leaders)	Markey share instability index			
	(1)	(2)	(3)	(4)	(5)	(6)
C20	0.1319***		-0.0865*			
	(0.0437)		(0.0474)			
C5		0.1652**		-0.0625		
		(0.0614)		(0.0479)		
Persistence rate (20 leaders)	-	-	-	-	-0.2236***	
	-	-	-	-	(0.0460)	
Persistence rate (5 leaders)	-	-	-	-		-0.2047***
	-	-	-	-		(0.0303)
KIA sector dummy	-0.0730**	-0.0953**	0.0573*	0.0511	0.0303	0.0271
	(0.0320)	(0.0432)	(0.0305)	(0.0318)	(0.0317)	(0.0311)
Business cycle	0.2086	0.0579	-0.6824***	-0.6824***	-0.6224***	-0.6538***
	(0.2466)	(0.3044)	(0.2064)	(0.2059)	(0.1805)	(0.1775)
Constant	0.7010***	0.6732***	0.3238***	0.3035***	0.4554***	0.4332***
	(0.0253)	(0.0225)	(0.0309)	(0.0245)	(0.0436)	(0.0335)
Observations	988	988	986	986	986	986

Notes: The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in each industry. The 'market share instability index' measures the summation of each industry's absolute change in market shares. The leadership persistence rate is defined as the ratio of market share leaders in "t" remaining in the leadership in t+1 to the total number of leading firms in "t". The industrial indicator of the business cycle is calculated as the weighted average of the cyclical component of the net job creation by region. The weighting factor is the number of firms in each region. Knowledge-intensive activities (KIA) are classified using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Industry-clustered errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Third, the results suggest that the higher the level of entrenchment of the dominant firms, the lower the instability of market shares. This relationship is highly statistically significant, meaning that sales accumulation may indirectly weaken competitive intensity through its positive effect on leadership persistence. Finally, we note that KIA industries appear to allow less leadership entrenchment while exhibiting more instability (although only the former correlation is very significant).

Table 6.2 presents the industrial regression outputs on the relationship between the leaders' relative productivity growth and the competitive regime. Since the relationship between concentration and industrial instability did not exhibit statistical significance, I included the concentration ratio as an additional covariate.[70] On the one hand, we observe that the greater

[70] Furthermore, the post-estimation tests rejected the hypothesis of collinearity among regressors.

the instability of market shares, the larger the productivity growth of dominant firms. On the other hand, the estimates suggest that a higher sales concentration of industrial leaders negatively correlates with their productivity growth. Both results are related to Aghion et al.'s (2001) escape-competition hypothesis, which claims that industry leaders have greater incentives to innovate when competition is more intense. Also, these findings support Arrow's (1962) replacement effect, which claims that increased market power entails a higher opportunity cost of continuing to innovate and, thus, a more entrenched conservative position.

Table 6.2 OLS industry-level regressions (2-digit) on the relationship between concentration and market share instability and leaders' productivity growth

Variables	Relative productivity growth (20 leaders)	Relative productivity growth (5 leaders)
	(1)	(2)
Market share instability index	1.1324***	1.8817***
	(0.1966)	(0.2844)
C20	-0.4470***	-
	(0.0988)	-
C5	-	-0.3512**
	-	(0.1346)
KIA sector dummy	-0.0358	-0.0731
	(0.0605)	(0.0984)
Business cycle	-1.7338***	-1.4472*
	(0.5959)	(0.7966)
Constant	0.1641***	-0.0642
	(0.0523)	(0.0601)
Observations	986	986

Notes: The 'market share instability index' measures the summation of each industry's absolute change in market shares. The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in each industry. Relative productivity growth is calculated as the logarithmic difference between firm and industry productivity growth. Knowledge-intensive activities (KIA) are classified using the methodology developed by Eurostat. Industries are defined on a time-consistent CAE Rev.2 basis. Industry-clustered errors in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

As discussed in the methodological section, I follow the evolutionary tradition that the innovation-market share growth relationship is critical for evaluating the competitive regime. Thus, the effect of concentration should be assessed along this dimension.

Table 6.3 accordingly shows the estimation results of the fixed effects panel regressions on the modified replicator dynamics function presented in equation (6.13), using RLP and TFP. Firstly, the results indicate that a larger market share translates into slower market share growth. Secondly, the RLP growth results suggest that young firms grow faster than mature ones (in line with the extant evidence), while those for TFP growth indicate the opposite.

Regarding the regressors directly associated with Schumpeterian competition, the results indicate that companies with above-average productivity growth expand their market share faster. For example, assuming a neutral economic cycle, specification (1) in Table 6.3 yields that a firm with an RLP growth of one standard deviation above the industry average grows 46 p.p. faster than the average company in the sector.[71] Additionally, we note that market selection is generally countercyclical. Thus, supporting the cleansing hypothesis, a slump seems to accelerate the downsizing (expansion) of less (more) innovative firms. However, this effect is only significant when using RLP growth.

We also observe that companies operating in more concentrated sectors exhibit more limited growth. This outcome holds using both concentration indices and with both efficiency measures. Finally, in specifications (2) to (6), we observe that the interaction between productivity growth and concentration ratio is negative and significant, meaning that the higher the concentration, the lower the innovation effect on expanding market share. In other words, the results seem to confirm our central hypothesis that market concentration weakens competition, which is paradoxical because (Schumpeterian) competition precisely leads to concentration. Moreover, since the magnitude of the interaction between productivity growth and the C5 index is larger than those of the C20 index, the findings suggest that the adverse concentration effect on the innovation-growth relationship is more significant when sales accumulation at the top of the structure is greater.

[71] Since productivity growth is relative to industry efficiency growth, we can estimate the market share growth differential between an 'innovative' firm and the industry average firm by multiplying all the regression coefficients of the productivity times the standard deviation of the sample. Therefore, assuming specification (1) and a neutral business cycle (i.e., the cyclical indicator set to zero), the growth differential is 46 p.p.

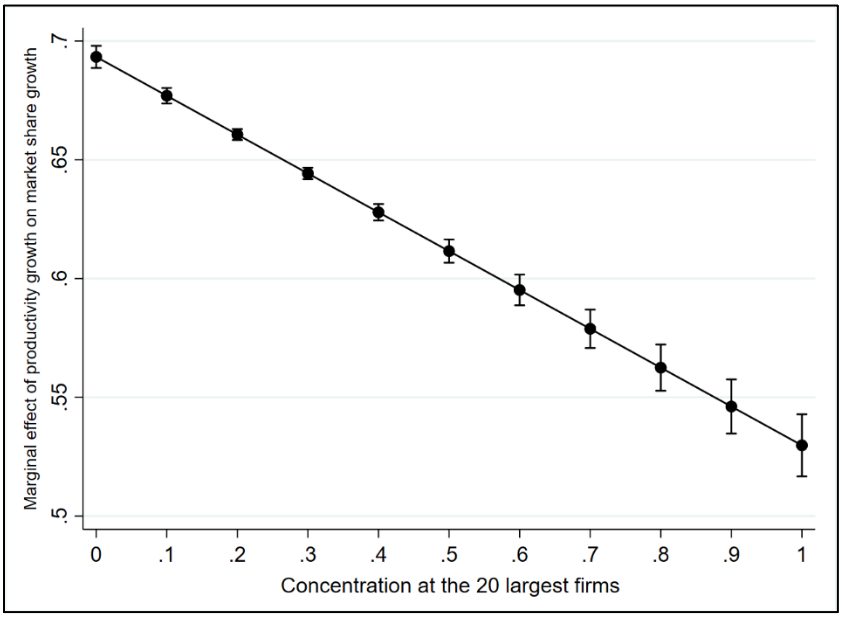
Table 6.3 Fixed effects panel regressions on the modified replicator dynamics function

Variables	Market share growth					
	Using RLP growth			Using TFP growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity growth	0.6544***	0.6933***	0.6918***	0.3183***	0.3797***	0.3788***
	(0.0011)	(0.0024)	(0.0020)	(0.0063)	(0.0148)	(0.0115)
C20		-0.4484***			-1.0561***	
		(0.0059)			(0.0490)	
Productivity growth × C20		-0.1636***			-0.2239***	
		(0.0087)			(0.0456)	
C5			-0.5717***			-1.0306***
			(0.0064)			(0.0480)
Productivity growth × C5			-0.2730***			-0.3707***
			(0.0117)			(0.0552)
Initial market share	-0.2508***	-0.2539***	-0.2539***	-0.5571***	-0.5622***	-0.5611***
	(0.0010)	(0.0010)	(0.0010)	(0.0037)	(0.0036)	(0.0037)
Young firms dummy	0.0204***	0.0201***	0.0196***	-0.0158**	-0.0173**	-0.0179**
	(0.0007)	(0.0007)	(0.0007)	(0.0076)	(0.0074)	(0.0074)
Business cycle	0.1365***	0.1364***	0.1323***	0.5517***	0.5226***	0.5126***
	(0.0146)	(0.0146)	(0.0146)	(0.1026)	(0.1042)	(0.1039)
Productivity growth × Business cycle	-0.3948***	-0.3589***	-0.3230***	-0.0537	-0.0043	0.0287
	(0.0241)	(0.0242)	(0.0242)	(0.1342)	(0.1236)	(0.1260)
Constant	-2.5172***	-2.4225***	-2.4669***	-5.8940***	-5.6668***	-5.8123***
	(0.0141)	(0.0140)	(0.0141)	(0.1458)	(0.1453)	(0.1436)
Observations	4,408,750	4,408,750	4,408,750	2,197,634	2,197,634	2,197,634

Notes: Market share refers to the proportion of industry sales (2-digit CAE). Market share growth is measured as log differences. Productivity growth is measured as log differences in RLP (or TFP). Revenue labour productivity (RLP) is computed as revenue per worker (in logs). Total factor productivity (TFP) is estimated by applying the semiparametric method proposed by Levinsohn and Petrin (2003), controlling for the endogenous exit. Productivity growth is expressed as a deviation from the average industry productivity growth. The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in the industry. Young firms are less than 5 years old. The business cycle measure refers to the cyclical component of the annual net job creation rate by region. Estimates of industry, location and year dummy variables are not reported. Industries are defined on a time-consistent CAE Rev.2 basis. All variables were winsorized at the 1st and 99th percentiles. All regressions use the estimated inverse propensity scores as sampling weights. Firm-clustered errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

To better understand this relationship, Figure 6.13 displays the marginal effect of productivity growth upon market share growth as a function of industrial concentration. To this end, we employ the results of specification (2) (i.e., using the RLP and the C20 ratio) and estimate margins at sample observed values for all the other covariates. The figure indicates that the market rewards innovative efforts less and less as industries become more concentrated. Since the C20 index increased from 22.5 to 29% over 2000-2018, estimates suggest that a company with one log point of productivity growth above the industry average would grow roughly 1.3 percentage points faster had concentration remained at the 2000 concentration level. Considering the concentration statistics differentiated by the industry's knowledge intensity, we notice that this situation is more critical in the KIA sector, where the C20 index reached almost 40% in 2018. Therefore, the competitive selection is likely to have decreased significantly in the KIA sector.

Figure 6.12 The marginal effect of productivity growth on market share growth as a (linear) function of industrial concentration



Note: The graph shows the marginal effect of productivity growth upon market share growth, evaluated at different levels of industry concentration. The predictions use the estimates from specification (2), that is to say, using the RLP and the C20 concentration ratio. The predictions employ the sample observed values for the rest of the covariates. Y axis does not start at zero.

Finally, Table 6.4 presents the model results differentiated by sectorial knowledge intensity (KIA vs Non-KIA) and firm age category (Young vs Mature). *First*, the findings relative to productivity growth and the key control variables are confirmed. *Second*, concentration's negative and highly significant effect on competitive selection is confirmed in all specifications. *Third*, the evidence suggests that sales concentration facilitates market share growth in the KIA sector, given the positive and highly significant coefficient associated with the concentration ratios. Sales accumulation, however, seems to weaken the innovation-growth relationship in the KIA sector to a greater extent than in the Non-KIA sector since the interaction coefficient is larger in the former. *Finally*, young firms find it more challenging to grow in concentrated markets than mature firms, as the concentration coefficient magnitude is greater in the former case. Yet, the adverse effect of concentration on selection has a similar magnitude in young and mature companies.

To sum up, these findings suggest that a greater concentration of sales favours the preservation of dominant positions. At the same time, industries with a greater entrenchment of leaders exhibit less market instability (i.e., are less competitive). Moreover, the evidence appears to indicate that the weaker the competitive regime, the lower the incentives for leaders to continue innovating. Indeed, as seen in Section 6.2.1, leading companies currently show productivity growth rates close to the industrial average. The regression results also suggest that greater industrial concentration undermines both firm expansion and the innovation-market share growth relationship. Accordingly, it seems that Schumpeterian competition leads to concentration, and then concentration weakens competition.

The implications of these findings are further analysed in Chapter 8.

Table 6.4 Fixed effects panel regressions on the modified replicator dynamics function (using RLP)

Variables	Market share growth							
	KIA Sector		Non-KIA sector		Young firms		Mature firms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Productivity growth	0.6546***	0.6634***	0.6736***	0.6727***	0.5302***	0.5301***	0.7204***	0.7166***
	(0.0071)	(0.0060)	(0.0025)	(0.0020)	(0.0042)	(0.0034)	(0.0032)	(0.0027)
C20	0.1986***		-0.6593***		-0.8101***		-0.4648***	
	(0.0248)		(0.0062)		(0.0185)		(0.0066)	
Productivity growth × C20	-0.0923***		-0.0323***		-0.1544***		-0.1692***	
	(0.0205)		(0.0092)		(0.0147)		(0.0119)	
C5		0.1154***		-0.8195***		-0.9174***		-0.5880***
		(0.0253)		(0.0068)		(0.0184)		(0.0072)
Productivity growth × C5		-0.1962***		-0.0476***		-0.2633***		-0.2681***
		(0.0275)		(0.0119)		(0.0190)		(0.0164)
Initial market share	-0.2967***	-0.2965***	-0.2467***	-0.2465***	-0.5490***	-0.5483***	-0.2215***	-0.2215***
	(0.0033)	(0.0033)	(0.0010)	(0.0010)	(0.0023)	(0.0023)	(0.0012)	(0.0012)
Young firms dummy	0.0113***	0.0113***	0.0184***	0.0182***	-	-	-	-
	(0.0023)	(0.0023)	(0.0007)	(0.0007)	-	-	-	-
Business cycle	0.2003***	0.1966***	0.0975***	0.0972***	0.0832**	0.0807**	0.1284***	0.1244***
	(0.0462)	(0.0462)	(0.0153)	(0.0152)	(0.0330)	(0.0330)	(0.0168)	(0.0167)
Productivity growth × Business cycle	-0.4545***	-0.4016***	-0.3548***	-0.3549***	-0.6067***	-0.5773***	-0.2816***	-0.2471***
	(0.0746)	(0.0752)	(0.0252)	(0.0252)	(0.0525)	(0.0523)	(0.0309)	(0.0309)
Constant	-2.3969***	-2.3963***	-2.2946***	-2.3546***	-5.7774***	-5.8679***	-2.0473***	-2.0931***
	(0.1898)	(0.1897)	(0.0144)	(0.0145)	(0.0386)	(0.0386)	(0.0168)	(0.0169)
Observations	517,546	517,546	3,891,204	3,891,204	1,393,718	1,393,718	3,015,032	3,015,032

Notes: Market share growth is measured as log differences. Productivity growth is measured as log differences in RLP. Revenue labour productivity (RLP) is calculated as revenue per worker (in logs), expressed as a deviation from the industry-year mean. The C20 (C5) concentration index denotes the share of sales at the 20 (5) largest firms in the industry (2 digits). Young firms are less than 5 years old. The business cycle measure corresponds to the cyclical component of the region's annual net job creation rate. Estimates of industry, location and year dummy variables are not reported. Knowledge-intensive activities (KIA) are classified using the Eurostat methodology. Industries are defined on a time-consistent CAE Rev.2 basis. All variables were winsorised at the 1st and 99th percentiles. All regressions use the estimated inverse propensity scores as sampling weights. Firm-clustered errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

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7 Impaired destruction: Financially distressed firms, insolvency regimes and market selection

7.1 The institutional reforms in response to the Great Recession

The financial nature of the Great Recession raised concerns about the macroeconomic impact of the low quality of firms' balance sheets—mirrored in a growing stock of non-productive loans (NPLs). Miller and Stiglitz (2010) suggested that many small businesses were likely to be inefficiently liquidated due to excessive leverage in the aftermath of the crisis, with assets transferred to less productive but "deep-pocket" agents. As a result, the negative shock was expected to be amplified (Krishnamurthy, 2009; Miller & Stiglitz, 2010). These concerns have been particularly relevant in European countries.

In reaction, the European Banking Authority (EBA) and the European Central Bank (ECB) deployed a series of actions to strengthen the prudential supervision of credit institutions in the Eurozone. In particular, the creation of a Single Supervisory Mechanism for banks in 2013 and the adoption of a standard definition of NPLs (and forbearance) for bank health assessment in 2015 (Jassaud & Vidon, 2017).

In addition to implementing the prudential supervision policies of the ECB, several European countries reformed their insolvency regimes to adopt business reorganization procedures similar to Chapter 11 of the US Bankruptcy Act. Following the recommendations of the European Commission and the International Monetary Fund to improve the efficiency of national insolvency regimes, the reforms particularly encouraged the reorganization of viable companies (Bergthaler et al., 2015; Carcea et al., 2015; McGowan & Andrews, 2018). In the case of Portugal, the reforms were first implemented in 2012.

The 2004 Insolvency and Company Recovery Code (CIRE by its acronym in Portuguese) was designed to prioritise the protection of creditors' rights, favouring liquidation over corporate restructuring. However, in 2012 and later years, the Portuguese authorities carried out reforms in CIRE to generate a shift in its orientation, stimulating business reorganization through solidifying the pre-bankruptcy regime. Specifically, the 2012 reforms included:

(i) A hybrid pre-insolvency mechanism (with judicial supervision) called "Special Revitalization Process" (PER by its acronym in Portuguese) to promote a fast-restructuring agreement between debtors and creditors in firms that are in an imminent insolvency situation, whose procedure can be initiated by both debtors and creditors;

(ii) Those creditors who inject new capital for restructuring have priority if the company is subsequently liquidated, that is, if reorganization fails; and

(iii) An Extrajudicial Business Recovery System (SIREVE by its acronym in Portuguese) focused mainly on SME, with technical support from the Portuguese Agency for Competition and Innovation (IAPMEI by its acronym in Portuguese).

Furthermore, early warning mechanisms have also been created in subsequent years. Specifically, the Bank of Portugal developed a mechanism for credit institutions to detect companies at 'risk of default' in 2014, while the IAPMEI created a tool for the financial self-assessment of firms in 2015. In addition, the legislation, before and after the reforms, contains in particular: (i) a "cram-down" for the approval of reorganization agreements, where dissident creditors receive at least what they would receive in liquidation; (ii) an "automatic-stay-on-assets" only for a limited interval; and (iii) managers are not dismissed during the reorganization process.

Overall, this set of measures sought timely insolvency statements and agile and efficient conflict resolutions while protecting the rights of creditors and debtors in a balanced manner. As a matter of fact, according to the OECD study conducted by McGowan and Andrews (2018), comparing the legislation in force in 2010 and 2016, Portugal is one of the countries that carried out greater efficiency reforms in its insolvency regulation, placing the country among the four OECD economies with the most efficient regimes. Furthermore, as stated by the European Commission study conducted by Carcea et al. (2015), Portugal is one of the most efficient countries, in regulatory terms, in the pre-insolvency regime (second only to the UK). The main improvement was in the "facility/availability of preventive measures" component.

Nonetheless, McGowan and Andrews (2018) note that the reform that allowed new financing during the restructuring process was not entirely adequate. The priority to new creditors was placed above all previous creditors and not just over the unsecured. This norm can adversely impact credit availability and legal certainty, contradicting the recommendations of the OECD. The authors also argue that although the Portuguese regime distinguishes between honest and fraudulent bankruptcies, it takes too long to discharge failed entrepreneurs. This fact makes bankruptcy a costly event, causing negative effects on timely insolvencies and future entrepreneurship (Armour & Cumming, 2008; McGowan & Andrews, 2018).

While the number of “bankruptcy, insolvency and recovery” processes was 14,010 between 2007 and 2012, this number increased to 25,661 in 2013-2018. Within them, 3,310 cases were related to PER procedures. Moreover, from the entry into force of SIREVE until 2018, 632 companies (98% of this total are SME) benefited from this out-of-court recovery mechanism, with 43% reaching an agreement in 7 months, on average. Though these official figures do not allow us to differentiate between zombie and non-zombie firms, they do offer a preliminary description of the evolution of the main procedures and an immediate measure of the impact of the implemented policy changes.

7.2 Methodology

7.2.1 Identification of zombie firms

Unviable firms are expected to recover or exit in a Schumpeterian competition setting. Hence, zombie survival likely reflects the extent of mobility barriers. This chapter explores how productivity growth and job creation react when destruction is impaired. In such a context, the definition of zombie firms is essential.

Following Carreira et al. (2022), zombie firms are defined as mature firms that are debt-ridden and have no potential to repay their debt due to a lack of profitability over an extended period. Several strategies have been proposed in the literature to identify which firms can be classified as zombies (see Carreira et al., 2022, for a survey). A common approach is the use of “profitability” and “evergreen lending” criteria proposed by Fukuda and Nakamura (2011). For example, Shen and Chen (2017) and Dai et al. (2019) define zombie firms as those that: (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 (negative operating profits for three consecutive years). Schivardi et al. (Schivardi et al., 2017) propose the use of the following “profitability” and “risk of default” criteria: (i) return-on-assets (measured as the three-year moving average of Earnings Before Interests, Taxes, Depreciations and Amortizations (EBITDA) over total assets) below the low-risk interest rate; and (ii) leverage above the median in the low return-on-assets exiting group.

A firm is classified as a zombie whenever: (i) its return-on-assets is lower than the low-risk interest rate for at least three consecutive years; (ii) its leverage is higher than the industry median (at two-digit level) of the low return-on-assets exiting group; and (iii) it is older than five years. The rationale is that firms that are already debt-ridden and have no potential to repay their debt are likely to be on the border of exit unless their creditors tolerate their continuation. The three-consecutive year criterion ensures that we are looking at persistently unprofitable firms. The age criterion distinguishes ‘true’ zombie firms from young start-ups (McGowan et al., 2017c). Lastly, the 5-year age threshold is chosen because it is the age limit used by several studies to define young, high-growth firms (Decker et al., 2016). Because the classification of zombie firms requires using financial variables that do not appear in QP, this process only applies to the SCIE dataset.

The *return on assets* is defined as EBITDA over total assets. EBITDA is what is left to remunerate capital after paying labour and intermediates inputs. I compare return-on-assets to the average Euribor-12-months interest rate, the indexing interest rate used by the Portuguese banking system. Leverage corresponds to the ratio of the sum of debt in current liabilities and long-term debt to total assets. Thus, the financial protection of zombie firms can come not only from bank forbearance but also from all types of creditors, a critical issue in the Portuguese economy.

To avoid potential misidentifications of zombie firms, one-shot zombie firms are excluded (i.e., one-off zombies), and one-shot restructuring firms are included (i.e., zombies that become non-zombies in t+1 and zombies again in t+2). Afterwards, I create the variable zombie spell, which corresponds to their lifetime in the zombie status (until recovery or exit). Moreover, since the identification strategy requires three consecutive observations, the estimation sample covers the 2005-2016 interval. To illustrate, a mature firm classified as a zombie in 2005 must show low profitability and a high risk of default in 2004 and 2006.

Finally, the Schivardi et al. (2017) definition is used for robustness checks, albeit including the additional 5-year age criterion.

7.2.2 Counterfactual model on the effect of insolvency reforms on zombie entrenchment

The empirical approach investigates whether a given set of institutional changes effectively reduces reallocation barriers. That is, whether the reforms can strengthen business dynamism and market selection through (i) a reduction in the zombie entrenchment, manifested in (ii) a greater recovery likelihood of financially distressed but viable firms and (iii) a higher exit probability of ‘true’ zombies. This chapter also aims to examine (iv) the responsiveness of reallocation to productivity before and after the reforms.

The inquiry begins by describing the zombie population’s characteristics and comparing them with non-zombie companies. Subsequently, it analyses the incidence of these financially distressed enterprises in the Portuguese economy from 2004 to 2017 and their impact on industrial productivity. Next, it deploys a failure-time analysis and estimates the extended means of survival spells using the methodology proposed by Klein and Moeschberger (2003).[72]

Later, the econometric strategy seeks to assess whether institutional reforms are effective in reducing the probability that a zombie in t remains in the same status in $t + 1$ (i.e., the entrenchment likelihood). Considering that the Schumpeterian creative destruction should compel zombies to recover or exit, I assume that the greater the zombie entrenchment, the higher the mobility barriers. The data enables observing the zombies that operated under the insolvency framework before the 2012 reforms (typically a more creditor-oriented regime) and the zombies that operated under the new institutional environment (legislation more balanced between debtors and creditors). However, a pure difference between the odds of entrenchment between pre- and post-reform zombies is likely to give us a biased assessment of the effect of institutional changes. For example, some characteristics of zombies, which influence the probability of entrenchment, might be expected to induce 'self-selection' in their 'participation' in the post-reforms period.

Hence, investigating the causal effects of reforms requires some speculation on what would have been the entrenchment likelihood of a zombie in the absence of reforms. I use the standard model of potential/counterfactual outcomes to tackle this issue (Cameron & Trivedi, 2005; Rubin, 1974). Thus, let us denote the insolvency framework faced by the zombies by the binary variable IR, with $IR = 1$ being the treatment level (the new insolvency environment) and $IR = 0$ the control level (the old regime). Additionally, let us denote the binary outcome variable as $Y_{i,t+1}$, which takes the value of one when the company leaves the zombie status in $t + 1$ (i.e., recovers or exits the market) and zero otherwise (zombie entrenchment). In this setting, we have then $Y_{1,i,t+1}$ if $IR = 1$ and $Y_{0,i,t+1}$ if $IR = 0$, that is:

$$\mathrm{Y_{i,t+1}} = (1 - \mathrm{IR})\mathrm{Y_{0,i,t+1}} + \mathrm{IR}\left(\mathrm{Y_{1,i,t+1}}\right), \tag{7.1}$$

[72] The failure event corresponds to recovering or exiting the market, and the survival time to the *entrenchment time* (i.e., the life duration as zombie). Since the largest observed analysis time is censored, I estimate the extended means of survival spells, which are computed by extending the Kaplan-Meier product-limit survival function to zero (Klein & Moeschberger, 2003). Firms that are flagged as zombies more than once are considered different subjects (only 6.6% of the total zombies during 2005-2016).

In addition, let us suppose that the probability that the outcome variable $\mathrm{Y_{i,t+1}}$ takes the value of one is a function of observed zombie characteristics and time-specific observed factors so that:

$$E\left[\mathrm{Y_{i,t+1}}\right] = P\left[\mathrm{Y_{i,t+1}} = 1|\mathbf{D_{i,t}}\right] = F\left(\mathbf{D_{i,t}}'\mathbf{B}\right), \tag{7.2}$$

where $\boldsymbol{D_{i,t}}$ is the matrix of predictors containing TFP (measured as deviation from the industry mean), capital, labour (employment), leverage, EBITDA (taken as a cash-flow proxy), and firm age (all variables in logs), as well as a business cycle measure (the annual growth rate of GDP in each of the Nomenclature of Territorial Units for Statistical Purposes (NUTS) level II) and industry and location dummies. The inclusion of a cyclical variable in the matrix $\boldsymbol{D_{i,t}}$ plays a crucial role in this setting. Furthermore, given that the treatment variable depends on the treatment period (after 2012), after controlling for the business cycle, the IR variable is expected to capture the effect of the institutional changes implemented by the ECB and the Portuguese authorities.

Finally, assuming conditional mean independence (i.e., $E\left[Y_{1,i,t+1}|\boldsymbol{D_{i,t}}, IR\right] = E\left[Y_{1,i,t+1}|\boldsymbol{D_{i,t}}\right]$ and $E\left[Y_{0,i,t+1}|\boldsymbol{D_{i,t}}, IR\right] = E\left[Y_{0,i,t+1}|\boldsymbol{D_{i,t}}\right]$) and common support (i.e., $0 < \mathrm{P}\left[\mathrm{IR} = 1|\mathbf{D_{i,t}}\right] < 1$), the average treatment effect (ATE) and the average treatment effect on the treated (ATET) are given by:

$$\mathrm{ATE} = \mathrm{E}\left[\mathrm{Y_{1,i,t+1}}|\mathbf{D_{i,t}}\right] - \mathrm{E}\left[\mathrm{Y_{0,i,t+1}}|\mathbf{D_{i,t}}\right], \tag{7.3}$$

$$\mathrm{ATET} = \mathrm{E}\left[\mathrm{Y_{1,i,t+1}}|\mathbf{D_{i,t}}, \mathrm{IR} = 1\right] - \mathrm{E}\left[\mathrm{Y_{0,i,t+1}}|\mathbf{D_{i,t}}, \mathrm{IR} = 1\right], \tag{7.4}$$

I apply the ‘regression adjustment’ and ‘nearest neighbour matching’ methods to obtain the average treatment effect and the average treatment effect on the treated. This procedure enables us to get the treatment effects without assuming any specific functional form for the treatment assignment process.

The *regression adjustment* estimator executes separate regressions for each treatment level and uses averages of expected outcomes for the whole sample to estimate potential outcome means (Cameron & Trivedi, 2005). Specifically, a linear probability model and a logistic regression are employed to predict the outcome variable. In the case of the ‘nearest neighbour matching’ estimator, a key aspect is to find for each unit *i*, and each treatment level, the nearest counterfactual unit *i’*. The *similarity* is computed by the Mahalanobis distance metric, which weights the differences by the inverse sample covariate covariance (Cameron & Trivedi, 2005). Moreover, since the matrix of predictors for the outcome variable contains several continuous covariates, the Abadie and Imbens' (2011) approach is employed to correct the resulting large-sample bias. Finally, exact matching on industry affiliation and location is imposed. I apply this procedure with one and two matches for each observed zombie.

To ensure that the treatment assignment does not correlate with the covariates that influence the outcome variable (the likelihood of exiting the zombie status, in this case), we must ensure that the predictors' distributions do not vary across treatment levels. Table C.1 of the Appendix section shows the predictors' standardized differences and variance ratios before and after matching (with one and two matches). The results reveal that the observations of the treated and counterfactual groups are much more balanced after the matching process, as the standardized differences of all covariates are close to zero and the variance ratios close to one.

7.2.3 *Multinomial analysis on zombie transitions and within-group selection*

The chapter subsequently investigates the determinants of zombie transition with a twofold objective. Firstly, it analyses whether the reforms efficiently strengthen the within-zombie selection (boosting the recovery of the most productive and the exit of the least productive). Secondly, it examines whether zombie entrenchment changes occur due to changes in the likelihood of recovery, exit, or both. For this purpose, a multinomial logistic model is deployed in which the base category is defined as 'remaining as a zombie', coded as 1. In contrast, recovery is coded as 2, and exit is coded as 3. Then, assuming independent and identically distributed error terms, the model is specified as follows (j = 1, 2, 3):

$$\Pr\left(Y_{i,t+1}=j\right)=\frac{\exp\{c_j+\psi_{0j}*IR_t+\mathbf{K}'_{i,t}\boldsymbol{\Phi}_j+[\mathbf{K}'_{i,t}\boldsymbol{\Psi}_j]*IR_t+\mathbf{W}'_{i,t}\mathbf{Z}_j\}}{\sum_{l=1}^{3}\exp\{c_l+\psi_{0l}*IR_t+\mathbf{K}'_{i,t}\boldsymbol{\Phi}_l+[\mathbf{K}'_{i,t}\boldsymbol{\Psi}_l]*IR_t+\mathbf{W}'_{i,t}\mathbf{Z}_l\}}, \tag{7.5}$$

where $\mathbf{K}_{i,t}$ contains the key explanatory variables TFP (or labour productivity), capital, labour, and leverage (all in logs), while $\mathbf{W}_{i,t}$ includes the control variables EBITDA and firm age (also in logs), business cycle, and industry- and location-dummies. The zombie spell variable is also considered an additional regressor. The explanatory variables are lagged for one period to avoid endogeneity generated by simultaneity bias (Carreira et al., 2022; Fukuda & Nakamura, 2011). The variable IR is included as an additional regressor in this setting. So, $IR = 1$ for the zombies under the new insolvency framework (2013-2016) and IR=0 for the previous regime (2005-2012). This inquiry is, in particular, interested in analysing the changes in the probabilities of transition, or non-transition, in the post-reforms period, as well as the effect of the reforms on the relationship between a given set of covariates (e.g., productivity, capital, labour, and leverage) and those probabilities, using the corresponding interaction terms.

I interpret the effects of the key explanatory variables on each transition likelihood, and the interaction effects in this nonlinear model context, based on the computation of average marginal effects (AME) (Karaca-Mandic et al., 2012). Since there are three transition categories, each regressor has three marginal effects. As is well-known, the marginal effects of each regressor add up to zero because probabilities add up to one (Cameron & Trivedi, 2010). This property conveniently allows us to examine which effect prevails. The AME of a one-unit change in κ_k on the probability that the destination j is the outcome in t+1 is given by:

$$\mathrm{AME}_{j\kappa_k\tau} = \frac{\partial \Pr(Y=j)}{\partial \kappa_k} = \frac{\partial p_j}{\partial \kappa_k}, \tag{7.6}$$

The subscript τ denotes the period, with $\tau = 0, 1, 2$ indicating the ex-ante and ex-post reforms periods and the entire sample period, respectively. κ represents the explanatory variables included in **K** by order, with $k = 1, \ldots, 4$.

While the marginal effects for the entire interval allow analysing the relationship between κ_k and the probability p_j, the pairwise comparison of marginal effects 'before' and 'after' permits studying the effects of the reforms on these relationships—i.e., the interaction effects (Karaca-Mandic et al., 2012). For instance, if $\mathrm{AME}_{j\kappa_k 1}$ and $\mathrm{AME}_{j\kappa_k 0}$ have the same sign, but the former is larger than the latter, the corresponding relationship is strengthened in the post-reforms period.

It is expected that the more productive zombies have a greater probability of recovery while the less productive ones have a greater exit probability. Moreover, one would expect the reforms implemented to strengthen this selection. Therefore, we expect $\mathrm{AME}_{2\kappa_1 1} > \mathrm{AME}_{2\kappa_1 0} > 0$ and $\mathrm{AME}_{3\kappa_1 1} < \mathrm{AME}_{3\kappa_1 0} < 0$. If $\mathrm{AME}_{2\kappa_1 1} - \mathrm{AME}_{2\kappa_1 0}$ is negative, it would imply that the reforms make the recovery event less likely despite an increase in productivity, which in turn would mean that the reforms impose higher barriers to the restructuring of viable firms. On the other hand, if $\mathrm{AME}_{3\kappa_1 1} - \mathrm{AME}_{3\kappa_1 0}$ is positive, we have that an increase in productivity is associated with a higher probability of exit in the post-reforms period, which implies that relatively more productive firms would have been inefficiently liquidated.

As discussed in the literature review, the effect of firm size is ambiguous. Due to large companies' complex ownership and debt structures, a negative relationship between size and the probability of both recovery and exit may be expected *vis-à-vis* continuing as a zombie. Moreover, regarding the exit probability, since smaller companies are more likely to be liquidated due to a more significant share of concentrated and secured debt, the negative relationship between size and exit probability is reinforced. However, since larger companies tend to have more resources and greater management capacity, one could expect that these firms have a higher likelihood of recovery and a lower risk of exit. On the other hand, considering that the reforms sought to facilitate reorganization agreements, they are expected somehow to reverse the effect of size on both events. Thus, we expect $\mathrm{AME}_{2\kappa_{2,3}1} > \mathrm{AME}_{2\kappa_{2,3}0}$ and $\mathrm{AME}_{3\kappa_{2,3}1} > \mathrm{AME}_{3\kappa_{2,3}0}$.

Financially distressed firms are less likely to recover and have a more significant exit hazard. Thus, leverage is expected to have a negative (positive) effect on the recovery (exit) probability. Nonetheless, suppose the incentive for injecting new financing in reorganising viable businesses is effective. In that case, this should result in healthier leverage ratios that increase the chances of recovery. Therefore, I expect $\mathrm{AME}_{2\kappa_4 1} - \mathrm{AME}_{2\kappa_4 0}$ to be positive, thus diminishing the negative effect of leverage on recovery. So, we have that debt has to be reduced faster than assets or, scilicet, assets have to grow faster than debt. Otherwise, the new financing (or debt restructuring) would worsen the firm financial conditions rather than improve them. Concerning the probability of exit, the lesser banking forbearance should further reduce the survival chances of zombies with high leverage levels. Hence, I expect a positive sign in $\mathrm{AME}_{3\kappa_4 1} - \mathrm{AME}_{3\kappa_4 0}$. Finally, since the reforms aim to facilitate the recovery of financially distressed but viable firms and the exit of unviable ones, the difference in expected probabilities 'before' and 'after' is assumed to be positive in both cases.

7.2.4 Panel regressions on the impact of zombie congestion on job reallocation

The ultimate goal of reducing zombie prevalence is strengthening business dynamism and market selection in the entire economy. Therefore, this section evaluates whether there is a statistically significant change in zombie incidence's negative effect on productivity-enhancing reallocation and aggregate efficiency growth by this channel.

The regression equation is based on a standard competitive selection setup in which, conditional on the initial state, more productive firms grow faster (Decker et al., 2018). Nevertheless, as Decker et al. (2018) emphasized, when frictions affect the firm's cost function—such as market congestion created by zombies—the responsiveness in that relationship is weaker. In a more general perspective, the basic idea is that exit barriers and congestion created by retained firms (which reduce prices and restrict access to resources) make firm growth less sensitive to productivity and innovation differentials. Thus, I evaluate the distortion caused by zombies, and the reforms' effect on the level of distortion, as follows:

$$\mathrm{Y}_{\mathrm{i,s,t+1}} = \mathrm{c} + \beta \mathrm{TFP}_{\mathrm{i,s,t}}{}^{\mathrm{r}} + \alpha_1 \mathrm{ZE}_{\mathrm{s,t}} + \alpha_2 \left(\mathrm{TFP}_{\mathrm{i,s,t}}{}^{\mathrm{r}} * \mathrm{ZE}_{\mathrm{s,t}}\right) + \left[\lambda_1 \mathrm{ZE}_{\mathrm{s,t}} + \lambda_2 \left(\mathrm{TFP}_{\mathrm{i,s,t}}{}^{\mathrm{r}} * \mathrm{ZE}_{\mathrm{s,t}}\right)\right] * \mathrm{IR}_{\mathrm{t}} + \mathbf{X}'_{\mathrm{i,s,t}} \mathbf{\Theta}_{\mathbf{D}} + \mu_{\mathrm{i}} + \varepsilon_{\mathrm{i,s,t+1}}, \tag{7.7}$$

where the subscripts *i* and *s* denote firm and sector (2-digit level), respectively; μ_i represents the time-invariant idiosyncratic characteristics of the firm, and it is assumed to be correlated with the matrix of covariates. The dependent variables are employment growth and capital growth in separate runs.[73] The TFP is the log deviation from the industry mean. **X** is the matrix of control variables and includes initial size (log of employment), business cycle, and industry- and location-dummies. When the dependent variable is capital growth, initial capital is added as a control. Since the sample comprises all the firms in this case (and not only zombies), the IR variable is not included as a direct regressor. Matrix **X** thus also contains year dummies. To avoid the cycle effects on selection contaminating responsiveness estimates (such as the cleansing effect of recessions), **X** also includes interaction between TFP and the business cycle variable.

The critical variable, ZE, denotes (industrial) zombie entrenchment. Unlike other studies in which zombie prevalence is measured as the percentage of industry resources in zombie firms (e.g., Caballero et al., 2008; McGowan et al., 2017c), this approach measures not only the sunk resources but also the average time that these resources are trapped in zombie firms as follows:

$$\mathrm{ZE}_{\mathrm{s,t}} = \sum_{\mathrm{z=1}}^{\mathrm{n}} \left(\frac{\mathrm{resource}_{\mathrm{z,s,t}}}{\text{total industry resource}_{\mathrm{s,t}}}\right) \times \text{Zombie spell}_{\mathrm{z,s,t}}, \tag{7.9}$$

[73] The firm growth in terms of employment and capital are measured as the log difference in annual-employment and real-capital between two consecutive years. All variables are winsorized at the 1st and 99th percentiles in the regression analysis below.

where the subscript *z* denotes zombies. Although a higher proportion of sunk resources is expected to be directly related to a higher level of entrenchment, this approach is likely to capture better the pervasiveness of barriers to exit or restructuring in each period and their effect on market selection. Yet, this approach also uses the variable ZE measured as the share of industry resources sunk in zombies as a robustness check.

The effect of zombie entrenchment on the responsiveness of firm growth to productivity is given by the cross derivative $\frac{\partial^2 \mathrm{Y}}{\partial \mathrm{TFP}\, \partial \mathrm{ZE}} = \alpha_2 + \lambda_2 * \mathrm{IR}$. Therefore, I expect a negative sign in α_2, implying that the greater the zombie entrenchment, the lower the responsiveness. Nevertheless, if the reforms effectively reduce the reallocation barriers, λ_2 is expected to be positive. I, therefore, anticipate a lower distortion created by zombies during the post-reforms period.

Finally, in the spirit of Decker et al. (2018), I graphically illustrate the implications of the reforms by calculating the effect of zombie entrenchment on the growth differential between a productive firm—a firm with TFP one standard deviation above its industry mean—and the average firm, before and after the reforms. These estimates are then compared with the within-industry productivity dispersion to interpret whether the changes in responsiveness have to do with a shift in the variance of technological shocks faced by firms or a difference in firm responses to those shocks.

7.3 Estimation results

7.3.1 The incidence of zombie firms in Portugal during the new century

Table 1 shows zombies' main economic and financial indicators, versus non-zombies, for the entire period and before, during, and after the Portuguese crisis. Note that the average zombie is less efficient, smaller (concerning production and inputs), with less liquidity, and relatively more indebted than its non-zombie counterpart. Indeed, regarding financial health, approximately 80% of zombies have negative equity (i.e., liabilities are higher than assets), indicating that most were on the verge of insolvency. Figure 7.1 additionally shows the kernel density estimate of total factor productivity and labour productivity distributions for the zombie and non-zombie populations. Again, zombies are less productive than non-zombies, with the corresponding TFP and labour productivity distributions located to the left of non-zombies.

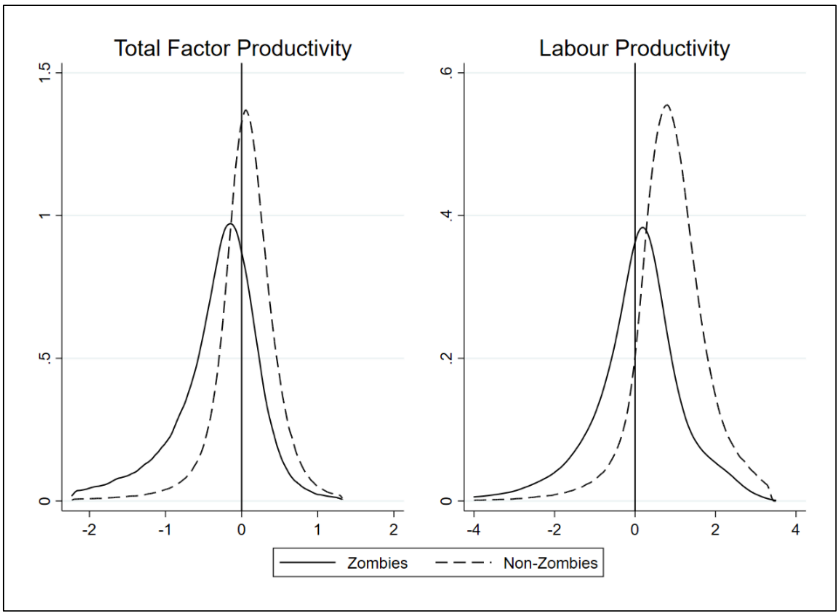
Figure 7.2 displays the annual share of zombies in the total number of Portuguese companies and two different weighted shares: capital and employment. As expected, zombie firms are pretty present in the Portuguese economy. On average, around 11 % of the companies in the sample were classified as zombies during the 2005-2016 interval. The largest share of zombies in the total number of firms was observed in 2012, possibly due to more remarkable forbearance during the financial crisis. Note, however, that the share of labour and capital sunk in zombies was maximum in 2006 and 2007, respectively, and that by 2016 the zombie share (either weighted or unweighted) was substantially reduced.

Table 7.1 Descriptive statistics of zombie- and non-zombie firms

Variable	Entire period (2005-2016)		Pre-crisis	Crisis	Post-crisis
	Mean	Std. Dev.	Mean	Mean	Mean
A. Non-zombies					
TFP	0.04	0.46	0.07	0.01	0.06
Labour productivity	0.99	0.85	1.05	0.96	0.99
Output	634.44	1726.30	671.88	621.32	622.26
Capital	1196.43	3352.85	1161.82	1223.22	1177.60
Number of employees	10.99	19.42	11.53	10.88	10.64
Age	12.81	10.49	10.54	12.90	14.98
EBITDA	70.64	219.45	76.90	66.48	72.65
Leverage ratio	0.81	0.85	0.77	0.81	0.85
Percentage of firms with negative equity	13.42%		10.83%	13.59%	15.75%
B. Zombies					
TFP	-0.36	0.67	-0.29	-0.39	-0.38
Labour productivity	0.32	0.60	0.44	0.30	0.22
Output	254.40	1013.75	373.77	240.50	158.77
Capital	846.72	2869.86	1083.24	846.47	593.83
Number of employees	6.86	13.32	8.15	6.83	5.53
Age	13.91	8.78	9.89	14.05	17.88
EBITDA	-26.54	77.84	-15.94	-29.79	-30.38
Leverage ratio	2.30	2.18	1.82	2.19	3.05
Percentage of firms with negative equity	79.48%		70.85%	79.60%	88.44%

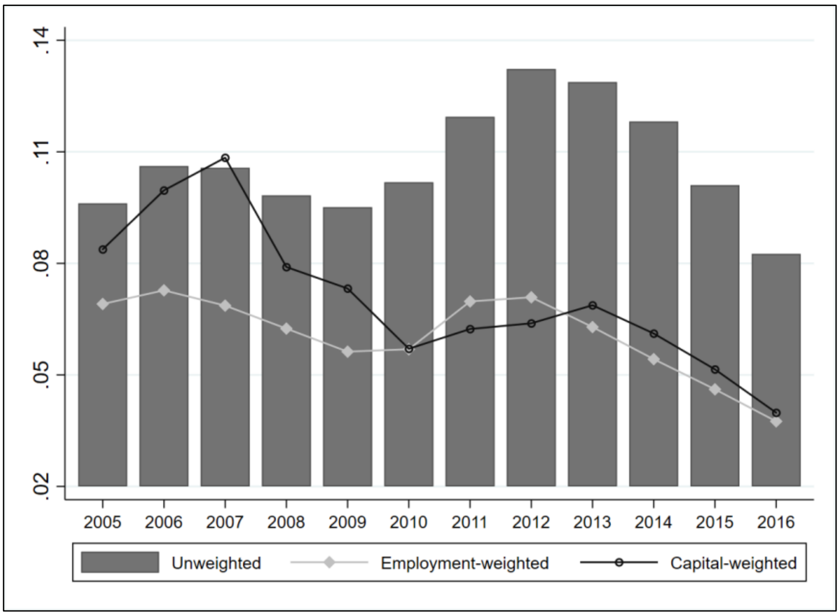
Notes: TFP and labour productivity are the deviations from the industry-year mean. The real output is the sales of good and services, adjusted for changes in inventory of final goods, self-consumption of own production and other operating revenues, deflated by industry-deflators (2-digit CAE). Real capital is measured using a perpetual inventory method to the change in total real assets. EBITDA denotes the earnings before interests, taxes, depreciation and amortization. The leverage is defined as the ratio of the sum of debt in current liabilities and long-term debt to total assets. A firm is flagged with negative equity when total debt is greater than total assets. Monetary values are in 10^3 Euros. All variables were winsorised at the 1st and 99th percentiles. Pre-crisis, Crisis, Post-crisis correspond to 2005-2007, 2008-2013, and 2014-2016, respectively.

Figure 7.1 Productivity distribution of zombie and non-zombie firms



Notes: Kernel density estimation. Total factor productivity and labour productivity are defined as the log deviation from industry-year mean. Variables were winsorized at the 1st and 99th percentiles. Pooled yearly values, 2005–2016.

Figure 7.2 The share of zombie firms, 2005-2016

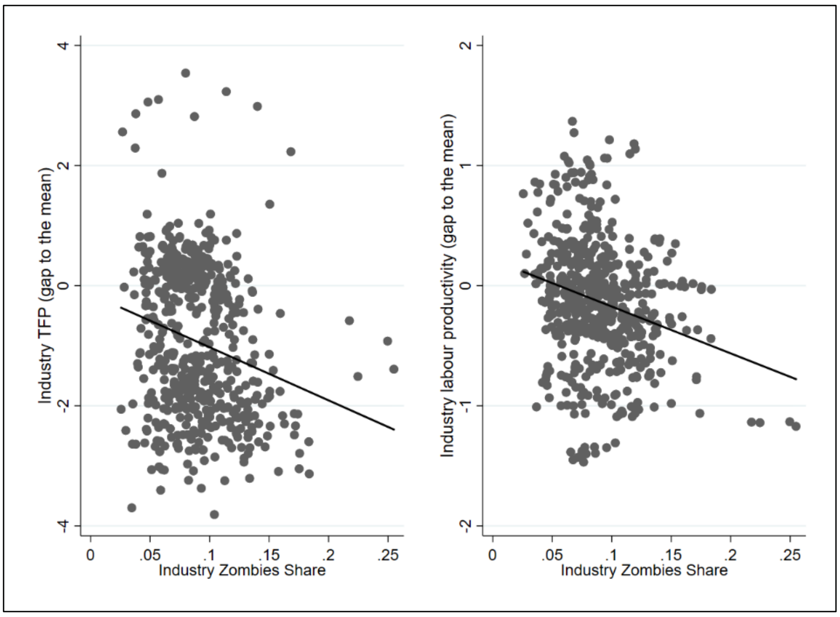


Notes: Zombies are defined as firms older than 5 years with a return-on-assets below the low-risk interest rate over three consecutive years and a leverage ratio above the industry median of the high-risk of default group. Capital and employment refer to the share pertaining to zombie firms.

As discussed, zombie firms hamper competition and allocative efficiency, thus generating lower aggregate productivity growth. Figure 7.3 examines the correlation between the proportion of zombie firms and the industry's year-level aggregate (weighted) productivity (in the two-digit CAE Rev. 2 classification). As can be seen, a higher proportion of zombies in an industry is associated with below-average industry productivity performance. According to the underlying estimates, a 1% decrease in the share of zombie firms implies a 0.5% (3.1%) increase in the industry's TFP (labour productivity).

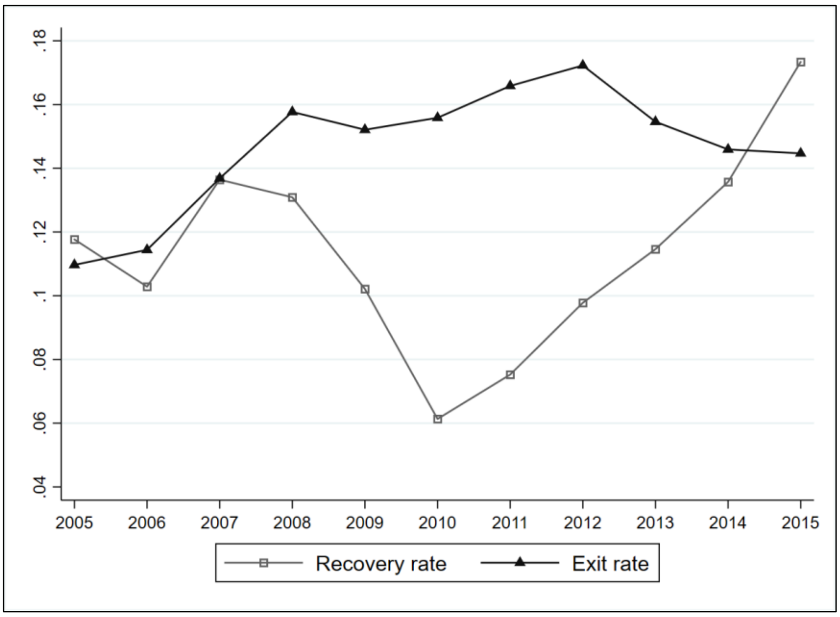
The evolution of the recovery and exit rates of zombie firms is shown in Figure 7.4. The recovery (exit) rate corresponds to the ratio of the total number of firms that were zombies in "t" and recovered (exited) in "t+1" to the total number of zombies in "t." First, the recovery and exit rates are relatively low throughout the selected interval, which means the "remain as a zombie" rate is quite high. Second, the exit rate increased to a maximum value of around 16% during the crisis and peaked at 17% in 2012, while the recovery rate dropped dramatically. These two aspects, plus the possible fall of new zombies, explain the observed rise in the share of zombie firms during the crisis. Third, there is a growing and sustained trend in the recovery rate after 2010, with a slight decrease in the exit rate after 2012.

Figure 7.3 The correlation between industry productivity and the share of zombie firms



Notes: Each dot reports industry productivity and zombies share at the industry-year level, at 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.

Figure 7.4 Recovery and exit rates of zombie firms



Notes: The unweighted-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.

Table 7.2 presents zombie firms' recovery and exit rates at the sector level. The previous values are broadly confirmed: by and large, in all sectors, the recovery rate decreased, and the exit rate increased during the crisis. Furthermore, the recovery rate in the post-crisis period is higher than that of the crisis and the pre-crisis. Regarding the exit rate, although this rate is higher in the post-crisis than in the pre-crisis, it is still lower than that of the recession period (except in the Business Services sector). In any case, the survival rate (i.e., remaining as a zombie) in the post-crisis period is lower than in the two previous sub-periods.

Table 7.2 Recovery and exit rate of zombie firms by sector and period (%)

Sector	Recovery rate			Exit rate		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
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

Notes: The reported values denote the unweighted-recovery (exit) rate of zombies which is defined as the ratio of zombies that recover (exit) in t+1 to the total number of zombie firms in t. Pre-crisis, Crisis, Post-crisis correspond to 2005-2007, 2008-2013, and 2014-2016, respectively.

Table 7.3 shows the distribution of employment-zombie and capital-zombie by size category. First, although large firms represent, on average, only 0.2% of the total of zombies, the share of employment and capital sunk in this size group is, on average, 14% and 10%, respectively, over the entire period. Second, by comparing the pre-crisis and post-crisis periods, the nature of the evolution of the zombie incidence was not homogeneous in terms of the resources sunk by size. Specifically, while the rate of reduction of zombie employment is lower in the case of micro-businesses, the rate of decrease of zombie capital is lower in medium and large firms. Therefore, in the post-crisis period, there is an increase in the relative share of micro firms and medium and large firms in the case of zombie-employment and zombie-capital, respectively.

Table 7.3 Resources sunk in the zombie population by size and period (%)

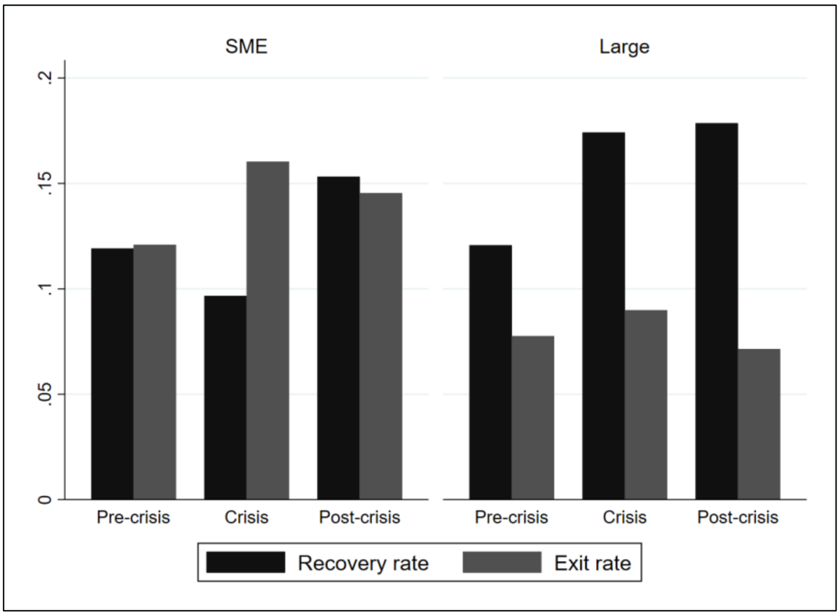
Size-category	All years (1)	Pre-crisis (2)	Crisis (3)	Post-crisis (4)	Change (p.p.) Pre- to Post-crisis (5) = [(4) – (2)]
A. Share of employment sunk					
Micro	40.38	34.35	40.02	47.14	12.79
Small	27.99	30.76	28.44	24.30	-6.46
Medium	18.12	17.44	19.20	16.64	-0.8
Large	13.51	17.45	12.34	11.92	-5.53
B. Share of capital sunk					
Micro	46.49	47.07	47.27	44.38	-2.69
Small	26.56	31.92	24.97	24.39	-7.53
Medium	16.60	15.16	16.84	17.56	2.4
Large	10.34	5.85	10.93	13.67	7.82

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 the European Union classification. Pre-crisis, Crisis, Post-crisis correspond to 2005-2007, 2008-2013, and 2014-2016, respectively.

The recovery and exit rates by size are presented in Figure 7.5. Three main results are in order: (i) SME have higher (lower) exit (recovery) likelihood than their large counterparts; (ii) in the crisis period, while the recovery rate of SME is reduced, it increases for large firms; and (iii) both small and large firms have increased their chances of recovery after the crisis. Therefore, it is clear that firm size plays a crucial role in restructuring versus liquidation in financially distressed businesses and, consequently, in the zombie incidence.

Table 7.4 reports the extended means of survival spells. Firstly, zombies require approximately three years and eight months to recover or exit the market (Column 1). Secondly, the findings suggest that reallocation barriers were reduced, as the survival time of zombies in the post-crisis period is shorter than those of the two previous intervals, both at the aggregate level and in all sectors.[74] Thirdly, the results unexpectedly show that the average zombie spell over the entire period is roughly three months longer for SME than for large firms. However, this difference appears to be explained by a substantial reduction in the zombie spell for large businesses and an increase in the spell for SME during the crisis. In the other two sub-periods, we observe that large firms have, on average, a longer survival time. Fourthly, the zombie spell post-crisis is also shorter than pre-crisis for both SME and large companies.

Figure 7.5 Recovery and exit rates by size and period



Notes: The size categories are defined according to the European Union classification. Pre-crisis, Crisis, and Post-crisis correspond to 2005-2007, 2008-2013 and 2014-2016, respectively.

Finally, as shown in Figure 7.6, preliminary evidence suggests that zombies under the new institutional setting experienced a lower probability of entrenchment than their counterparts from the previous regime. Conditional on the business cycle, the survival function of the former is below that of the latter. For instance, while a company that has been three years in zombie status under the old regime has an entrenchment likelihood of approximately 56%, its post-reform counterpart has an entrenchment chance of 49%.

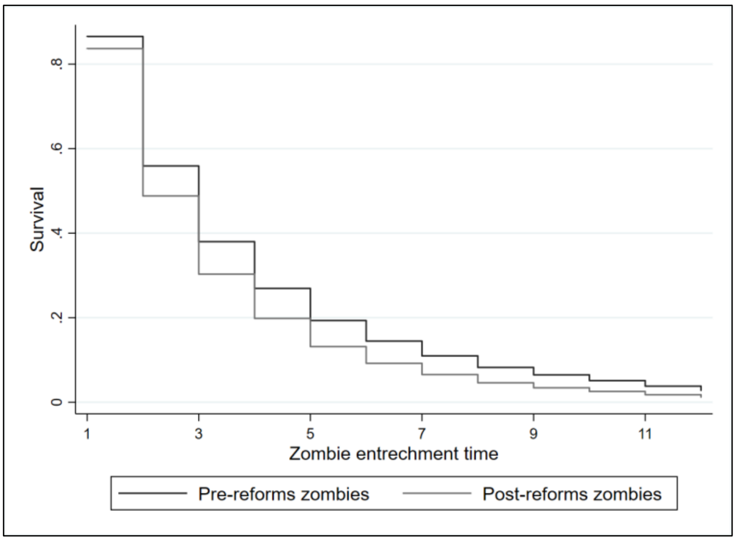
[74] Except for *Accommodation and Food Services*, where there was a slight increase of 1% in the survival time in the post-crisis period in comparison with the pre-crisis period.

Table 7.4 Estimated survival time of zombies

	Full period (1)	Pre-crisis (2)	Crisis (3)	Post-crisis (4)	Relative change (%): Post- to Pre-crisis (5) = [(4) / (2)]	Relative change (%): Post-crisis and Crisis (6) = [(4) / (3)]
Entire economy	3.62	3.68	3.87	2.91	-21%	-25%
A. By industry						
Manufacturing	3.63	3.56	3.72	3.33	-7%	-11%
Construction	3.20	3.22	3.24	2.95	-8%	-9%
Trade	3.92	3.97	3.94	3.52	-11%	-11%
Accommodation	4.87	4.17	5.53	4.19	1%	-24%
Real estate	3.65	3.81	3.66	3.32	-13%	-9%
Business services	3.39	3.43	3.40	3.20	-7%	-6%
B. By size						
SME	3.79	3.68	3.87	3.51	-4%	-9%
Micro	3.80	3.71	3.87	3.54	-5%	-8%
Small	3.61	3.53	3.80	3.17	-10%	-17%
Medium	3.92	3.36	4.13	3.82	14%	-7%
Large	3.57	4.13	3.38	3.79	-8%	12%

Notes: The reported values denote extended means of zombie spell (in years), using the method of Klein and Moeschberger (2003), which is computed by extending the Kaplan-Meier product-limit survival curve to zero. The size categories are defined according to the European Union classification.

Figure 7.6 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 business cycle. The survival function reports the probability of surviving (as zombie, in this case) beyond t.

7.3.2 Changes in zombie entrenchment: Treatment effect of reforms and transition probabilities

The previous section showed differences between crisis and post-crisis transitions. Therefore, it is important to find out what part of the changes in the recovery and exit of zombies is explained by the cycle and what part by the reforms. This section focuses on the second question.

Table 5 presents the estimations of average treatment effects (ATEs) and average treatment effects on the treated (ATETs) of the reforms on the probability of exiting the zombie status (via recovery/exit). We observe that the treatment effects are highly significant, showing that zombies *treated* by the new institutional framework (insolvency regime and prudential banking supervision) exhibited a greater likelihood of leaving the zombie status than their counterfactual zombies (under the old framework). In other words, the treatment reduced the chances of entrenchment. For instance, in the case of the 'nearest neighbour matching' (NNM) estimator of one match, the results suggest that the reforms increased the likelihood of exiting the zombie status, on the treated zombies, by 10.2 percentage points (i.e., in relation to non-treated zombies). Therefore, these results indicate that the new institutional setting promoted by the European and Portuguese authorities had a *causal effect* in reducing the zombie entrenchment, thus decreasing the reallocation barriers that facilitate the survival of these otherwise insolvent firms.

Table 7.5 Average treatment effects and Average treatment effects on the treated of the reforms on the probability of exit from the zombie status

Effect	Regression adjustment (RA)		Nearest neighbour matching (NNM)	
	LPM	Logit	One match	Two matches
ATEs	0.0680***	0.0730***	0.0668***	0.0656***
	(0.0026)	(0.0025)	(0.0036)	(0.0033)
ATETs	0.0636***	0.0667***	0.1021***	0.1009***
	(0.0026)	(0.0027)	(0.0036)	(0.0032)
Observations	198,104	198,104	198,104	198,104

Notes: The binary outcome variable takes the value of 1 if the company leaves the zombie status in $t+1$ (i.e., recovers or exits the market) and 0 otherwise (i.e. zombie entrenchment). The covariates for the outcome variable contain TFP (as deviation from the industry mean), capital, labour (employment), leverage, EBITDA (as a cash-flow proxy), and firm age (all in logs), as well as a business cycle measure (the annual growth rate of GDP in each region - NUTS II) and industry and location dummies. In the NNM case, the similarity is computed by the Mahalanobis distance metric. The Abadie and Imbens' (2011) approach is used to correct the large sample bias. It was imposed exact matching on industry affiliation and location. The covariates were winsorized at the 1st and 99th percentiles. Robust standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

While institutional reforms have proven effective in reducing zombie survival, it remains to be seen whether the lower entrenchment was due to a higher probability of recovery, exit, or both. Moreover, a key element to observe is the reforms' efficiency. The designed mechanisms must ensure a screening process that reduces information asymmetries and perverse incentives so that the most productive zombies recover easily. Furthermore, in the case of the exit transition, the implemented reforms are expected to prevent viable companies from being inefficiently liquidated and facilitate the liquidation of the 'true' zombies. The multinomial analysis allows examining these aspects.

Table 6 shows the main post-estimation results obtained from the multinomial regression model. In particular, the expected probabilities for each transition, the average marginal effects (AME), and the interaction effects—i.e., the (average) differences between pre- and post-reforms. First, the model's predictions for the entire sample period show that the probability of remaining as a zombie is approximately 73%, which is about 5 to 6 times larger than in the other two alternative transitions (i.e., recovery and exit). Yet, in line with the treatment effect model, estimations show that the entrenchment of a typical zombie decreases after the reforms. The "remain as a zombie" probability is 75.02% for zombies under the old regime (IR = 0), whereas it is 66.94% for zombies under the new framework (IR = 1). So, a decrease of 8.08 percentage points. It is worth noting that the reduction in the entrenchment likelihood is mainly explained by an increase of 6.12 percentage points in the recovery probability. In comparison, the increase in the exit likelihood is 1.96 percentage points.

Second, as expected, the more (less) productive the zombies are, the more likely the recovery (exit), *vis-à-vis* remaining as a zombie. Moreover, as shown in Column (4) of Table 6 (pairwise comparisons), the difference in marginal effects of TFP upon conditional recovery likelihood—before and after—is positive (at 2.71 percentage points) and highly statistically significant, which means that the more productive zombies are even more likely to recover after the reforms. In the case of exit, contrary to the hypothesis, the difference in AME is significantly positive. Indeed, although a one-unit change in TFP is still associated with a decrease in exit probability of 6.41% in the post-reforms period, this decrease is smaller than the corresponding of the pre-reforms period, at 7.43%. Since the base category is non-transition, the pairwise comparison results show that the less productive zombies become 1.03 percentage points less (more) likely to exit (remain as a zombie). Thus, the estimates indicate that the within-zombie selection at the exit margin has weakened—or that potentially viable firms were inefficiently liquidated after the reforms.[75]

[75] As a robustness test, Table C.3 in the Appendix, I present the results using labour productivity. The finding is confirmed.

Third, the greater the zombies' financial distress, the lower (higher) the likelihood of transition into recovery (exit). The pairwise comparison of AME between periods is statistically negative in both cases (-3.75 and -0.61 percentage points, respectively). Apparently, from this perspective, the reforms were not efficient. These results suggest that instead of reducing creditor forbearance, it has increased. Also, attempts to refinance the debt appear unsuccessful, favouring rather a greater probability of zombie survival. As a result, the interaction effect on the "remain as a zombie" likelihood is positive and highly statistically significant.

Table 7.6 Expected probabilities, average marginal effects, and differences between pre- and post-reforms periods, multinomial logistic regression

Covariate	Transition	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Pairwise comparison (Post minus Pre-reforms) (4)
A. Expected probabilities: $\Pr(Y_{i,t+1} = j)$					
	Remain as 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 (AME): $\partial p_j / \partial \kappa_k$					
TFP	Remain as 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 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 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 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: TFP, Capital, Labour and Leverage are in logs. IR is a dummy for the post-reforms zombies. The pairwise comparison between marginal effects express the interaction effect, that is, the difference in effects between the "zombies after the reforms" and the "zombies before the reforms". Unreported are estimates of control variables including log of EBITDA, log of age, log of zombie duration, business cycle, industry- and location-dummies. *** p<0.01, ** p<0.05, * p<0.1.

Finally, the effects of firm size on the zombie's transitions are addressed. The larger the firm (proxied by capital and labour), the greater (lower) the probability of recovery (exit). However, since the size effect on the exit likelihood is more significant than on the recovery likelihood, there is a positive relationship between size and non-transition probability, which is consistent with the hypothesis that the larger the company, the more likely it is to remain in the zombie status. Nonetheless, the reforms' effects on the recovery and exit likelihoods go in opposite directions, depending on whether the size is in terms of capital or employment. The positive (negative) relationship between capital and recovery (exit) is reduced by 0.77 (0.99) percentage points in the post-reforms period. On the other hand, the positive (negative) relationship between employment and recovery (exit) increased by 1.46 (1.21) percentage points after the reforms.

To deepen this issue, I follow Williams (2012) and compute the adjusted conditional probabilities at representative values of the (log) capital and (log) labour in the pre- and post-reforms periods. Table 7 reports the adjusted predictions for each transition of two zombies that only differ in the value of the corresponding firm size variable (to make it close to the marginal effect concept). The representative values are given by the average sample value of each covariate by size category (SME and large zombies).

According to Column (4) of Table 7 (differences in expected probabilities between pre- and post-reforms), the recovery likelihood of an average small-in-capital zombie raises 6.22 percentage points in the post-reforms interval. In contrast, the increase is only 3.11 percentage points in a typical large-in-capital zombie. It seems then 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 recovery probability is higher in small-in-capital zombies. Estimates suggest that the impact of the reforms—encouraging a reorganisation agreement—is more significant in small-in-capital businesses, probably because the number of creditor classes is lower in this type of firm, simplifying coordination. Additionally, since the larger the capital, the more outstanding the debt (in absolute terms), the resolution of financial distress is relatively delayed. But note that the effect of the institutional changes is also positive in large, financially distressed firms.

In the case of exit, although the liquidation probability increases in both types of zombies, the rise is 2.82 percentage points superior in those large-in-capital (see the pairwise comparison in Column 5). The exit likelihood of a typical small zombie increases from 14.04% to 16.23%, while this probability rises from 8.04% to 13.05% in the average large zombie. Thus, even though the negative relationship between capital size and exit likelihood holds after the reforms, the exit-risk gap between large and small financially distressed firms is reduced. This finding suggests that SME were relatively less prone to liquidation. As the increase in exit probability is more than twice as high in large companies, it seems that capital intensity also plays a vital role in the changes in liquidation probability.

Regarding employment size, the upsurge in the recovery probability of an average large-in-employment zombie is 4.72 percentage points higher than its small counterpart (pairwise comparison in Column 5 of Table 7). Thus, due to commanding more resources and increased managerial capabilities, large companies seem to achieve a successful restructuring in a shorter time, taking advantage of the new institutional framework. Concerning the exit transition, only the change in expected probabilities in the representative SME is statistically significant, and its exit likelihood increases by 1.90 percentage points in the post-reforms period. Therefore, the negative relationship between size-in-employment and liquidation probability increases after the institutional reforms, suggesting that the "too-big-to-fail" effect is likely to have played a crucial role in insolvency events.

Table 7.7 Expected probabilities at average size (capital and labour), Multinomial Logistic Regression

Variable	Transition	Size	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Difference in expected probabilities (4) = [(3) – (2)]	Pairwise comparison (Large vs SME) (5)
Capital	Remain as 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 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: IR is a dummy for the post-reforms zombies. Columns (1), (2) and (3) reports the estimated probabilities for the "average" firm in each representative value (sample average of ln(capital) and ln(labour)), where "average" means that the estimate is conditional on the 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. Unreported are estimates of TFP, leverage and the control variables including log of EBITDA, log of age, log of zombie duration, business cycle, industry and location dummies. Standard errors (not reported) for statistical significance tests are obtained using the delta-method. *** p<0.01, ** p<0.05, * p<0.1.

To further confirm that no confounding variables affect the interpretation of institutional changes' effectiveness, Table C.4 in the Appendix presents the results of a multinomial specification implemented in two subsamples, namely high turbulence industries and low turbulence industries, respectively. Following Gouveia and Osterhold (2018), I assume that sectors with a higher degree of turbulence (with more intense entry and exit rates) are more exposed to reforms of insolvency regimes. In other words, the impact of reforms on more turbulent industries is expected to be greater than that of their less turbulent counterparts. The results indicate that a greater probability of recovery and exit in both sectors reduced the entrenchment likelihood. However, as hypothesized, the reduction in the zombie survival likelihood was almost 0.7 p.p. greater in high-turbulent industries than in less turbulent ones. This more significant reduction in zombie entrenchment in the former is mainly due to a more substantial recovery probability (1.1 percentage points higher in the high turbulent sector). Finally, the reforms' interaction effect on the relationship between productivity and the recovery and exit likelihoods, more than having been noticeably greater, was only statistically significant for high turbulence industries (at the 1% level). As found in the entire sample, the reforms efficiently encouraged the recovery of the most productive zombies, albeit they were less efficient in the exit transition.

Overall, the results suggest that the reforms effectively reduce the barriers that hinder zombies' transition to recovery and exit. Moreover, since not all zombies are unviable firms, the implemented reform package (aimed at balancing debtors' and creditors' rights) reveals a more appropriate and efficient route. It encourages reorganization to prevail over liquidation in financially distressed firms (note that zombie entrenchment is reduced mainly by a greater recovery probability of the more productive zombies). Simultaneously, large and small companies increase their reorganization likelihood, indicating that the reforms mitigate delays in resolving insolvency conflict characteristic of large companies with many creditors and somehow complement the lower bargaining power of small businesses. Nevertheless, a misleading selection at the exit margin also reduces the zombie prevalence, as more productive firms are not risk-free from liquidation.

The debate on zombie companies has focused mainly on exit barriers. However, the results indicate that not all zombies are unviable firms. As many are just financially distressed, a creditor-centred regime may thus favour less productive but deep-pockets agents. Indeed, these results highlight that a proper balance between debtors' and creditors' rights is critical to ensure that inefficient liquidation does not prevail in financially distressed firms.

To examine whether the estimations are sensitive to the definition of zombie firms, I performed robustness checks using the criteria of Schivardi et al. (2017) (see Tables C.5 and C.6 in the Appendix). Despite the differences in magnitude, the findings show that both the sign and statistical significance of the main results hold.

7.3.3 *Post-reform reallocation across the economy*

The previous sections show that institutional reforms discourage zombie firms' entrenchment. Tables 7.8 and 7.9 now show the results of the linear fixed-effects panel regressions in which I analyse the effect of zombie prevalence on the economy-wide reallocation of employment and capital, respectively, using model (6).

Regarding employment growth, Table 8 presents that a higher level of idiosyncratic productivity is linked to higher firm growth, given by the highly significant and positive TFP coefficient in all specifications. Since the TFP is relative to the annual industry mean, if we multiply all the regression coefficients by the within-industry standard deviation, we can estimate the growth differential between a "productive" firm and the average firm in the sector (Decker et al., 2018). Thus, assuming specification (2) and a scenario of a zero-zombie share and neutral economic cycle (i.e., the cyclical indicator set to zero), the growth differential is 8.66% $[= 0.1345 \times S.D.(TFP^r)]$.[76]

As expected, the zombie entrenchment undermines the responsiveness of employment growth to productivity, as the TFP-ZE interaction term (either weighted by employment- or capital-sunk) is negative and highly statistically significant. However, the adverse impact of the zombie entrenchment on responsiveness seems to have been attenuated after the reforms, as the coefficient associated with the TFP-ZE-IR interaction term is significantly positive—Columns (2) and (4) of Table 7.8. Therefore, the results suggest that the reduction in responsiveness caused by zombies is lower after the reforms. In other words, the decline in entrenchment barriers is also translated into a lower distortion in selection and reallocation in the entire economy. Specifically, as Figure 7.7 shows, the zombie entrenchment (sample average) is associated with a reduction in the growth differential—between the productive and the average firm—of 2.77% in the pre-reforms interval $\{= S.D.(TFP^r) \times [-0.2644 \times \text{mean}(ZE)]\}$, whereas the reduction is only 1.37% in the post-reforms interval $\{= S.D.(TFP^r) \times [(-0.2644 \times \text{mean}(ZE)) + (0.1334 \times \text{mean}(ZE))]\}$.[77]

[76] The standard deviation of relative TFP during the selected interval is 0.6437. To abstract from changing TFP dispersion, I use the sample average value.

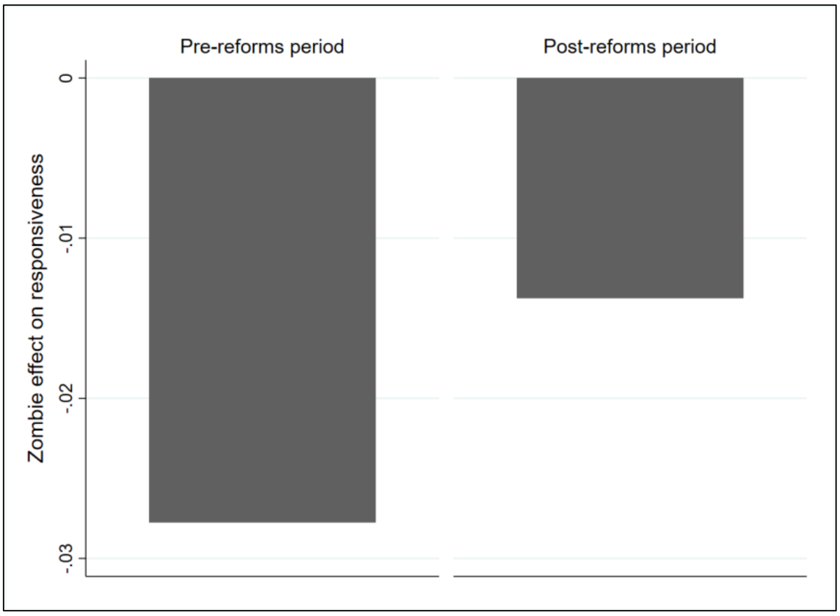
[77] The average sample value of the employment- and capital-weighted ZE are 0.1627 and 0.2042, respectively.

Table 7.8 Employment growth, fixed-effects panel regression

Variable	(1)	(2)	(3)	(4)
TFP	0.1221***	0.1345***	0.1026***	0.1043***
	(0.0023)	(0.0024)	(0.0015)	(0.0015)
Employment-weighted ZE	–0.0665***	–0.0838***		
	(0.0068)	(0.0096)		
TFP × Employment-weighted ZE	–0.1276***	–0.2644***		
	(0.0103)	(0.0143)		
Employment-weighted ZE × IR		0.0235**		
		(0.0094)		
TFP × Employment-weighted ZE × IR		0.1334***		
		(0.0091)		
Capital-weighted ZE			–0.1278***	–0.1010***
			(0.0039)	(0.0045)
TFP × Capital-weighted ZE			–0.0204***	–0.0370***
			(0.0041)	(0.0053)
Capital-weighted ZE × IR				–0.0362***
				(0.0034)
TFP × Capital-weighted ZE × IR				0.0176***
				(0.0050)
Observations	1,742,104	1,742,104	1,742,104	1,742,104
R-squared	0.1971	0.1973	0.1979	0.1980
Number of firms	245,885	245,885	245,885	245,885

Notes: Fixed-effect panel data model. Employment-growth is measure as difference in logs. ZE denotes zombie entrenchment. Employment- and capital-weighted ZE are measured as employment- and capital-weighted averages of zombie spell by industry (2-digit CAE). IR is a dummy for the post-reforms zombies. Unreported are estimates of control variables (log of employment, business cycle, interaction between TFP and business cycle, year-, industry- and location-dummies). The variables were winsorized at the 1st and 99th percentiles. Firm-cluster standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Figure 7.7 Zombie effect on the responsiveness of employment growth to productivity differences



Notes: Cross derivative between industry-ZE and productivity on employment-growth, evaluated at the standard deviation of TFP and the sample average employment-weighted ZE (2005-2016).

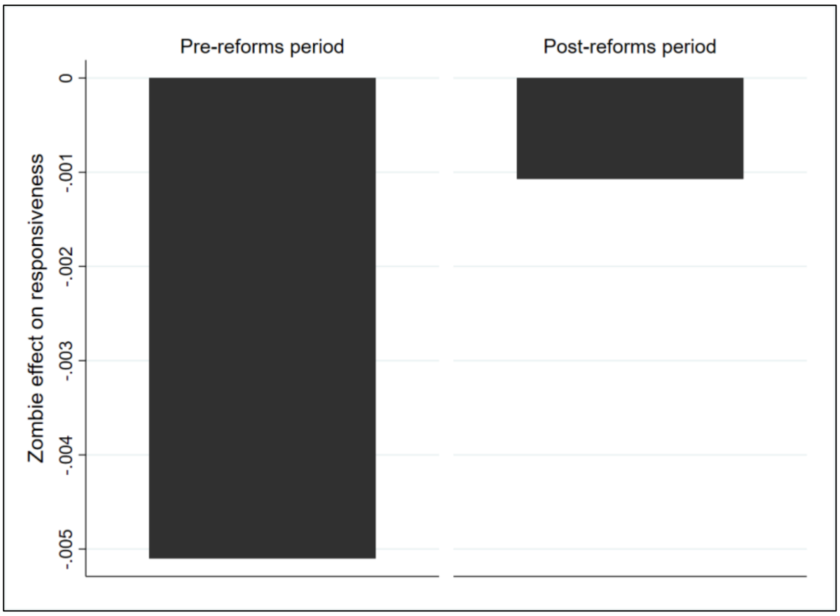
Capital reallocation estimates are in the same direction (Table 7.9). The capital growth differential between a productive and the average firm, without zombie and cyclical effects, is 4.21% $[= 0.0654 \times S.D.(TFP^r)]$. The regression results also show that zombie entrenchment's negative effect on capital growth's responsiveness to productivity decreases during the post-reforms interval: from 0.5% to 0.1%, *before* and *after* reforms, respectively (Figure 7.8).

Table 7.9 Capital growth, fixed-effects panel regression

Variable	(1)	(2)	(3)	(4)
TFP	0.0638***	0.0654***	0.0480***	0.0607***
	(0.0016)	(0.0016)	(0.0023)	(0.0025)
Capital-weighted ZE	–0.0696***	–0.0643***		
	(0.0038)	(0.0044)		
TFP × Capital-weighted ZE	–0.0170***	–0.0387***		
	(0.0039)	(0.0053)		
Capital-weighted ZE × IR		–0.0071**		
		(0.0033)		
TFP × Capital-weighted ZE × IR		0.0306***		
		(0.0050)		
Employment-weighted ZE			–0.1992***	–0.1795***
			(0.0076)	(0.0100)
TFP × Employment-weighted ZE			0.0569***	–0.0822***
			(0.0107)	(0.0144)
Employment-weighted ZE × IR				–0.0248**
				(0.0097)
TFP × Employment-weighted ZE × IR				0.1334***
				(0.0093)
Observations	1,742,104	1,742,104	1,742,104	1,742,104
R-squared	0.1680	0.1681	0.1685	0.1687
Number of firms	245,885	245,885	245,885	245,885

Notes: Fixed effect panel data model. Capital-growth is measure as difference in logs. ZE denotes zombie entrenchment. Capital- and employment-weighted ZE are measured as capital- and employment-weighted averages of zombie spell by industry (2-digit CAE). IR is a dummy for the post-reforms zombies. Unreported are estimates of control variables (log of employment in t, log of capital in t, business cycle, interaction between TFP and business cycle, year-, industry- and location-dummies). The variables were winsorized at the 1st and 99th percentiles. Firm-cluster standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

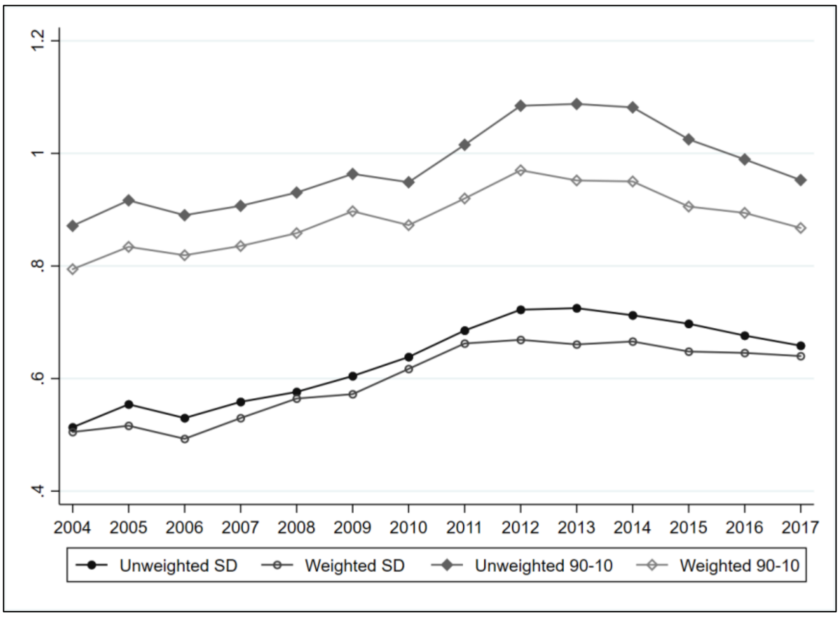
Figure 7.8 Zombie effect on the responsiveness of capital growth to productivity differences



Notes: Cross derivative between industry-ZE and productivity on capital growth, evaluated at the standard deviation of TFP and the sample average capital-weighted ZE (2005-2016).

Finally, Figure 7.9 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). Although there is a growing trend in productivity dispersion over the entire sample period, there has been a slight reduction since 2013. This reduced dispersion is consistent with the prediction that, under fewer reallocation barriers, the productivity gap between zombies and non-zombies is smaller, reducing the within-industry productivity dispersion (Caballero et al., 2008). In addition, this result is also consistent with the responsiveness hypothesis of Decker et al. (2018), who have 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 technological dispersion lower.

Figure 7.9 Within-industry TFP dispersion



Notes: Standard deviation and 90-10 differential of within-industry log TFP (as a deviation from the industry mean). Unweighted and weighted measures (output-industry shares as weights).

In a nutshell, the estimates from the fixed-effects panel regression show that the negative effect of zombie entrenchment on the responsiveness of firm growth (in terms of employment and capital) to productivity is reduced in the post-reforms period, which is accompanied by a slight decrease in the within-industry productivity dispersion. In other words, as the reallocation barriers decrease, their adverse impact on productivity-enhancing resource reallocation decreases too.

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8 Conclusions, policy implications and future research: Connecting creative destruction trends

Schumpeter claimed that creative destruction is the "fundamental impulse that sets and keeps the capitalist machine in motion" (Schumpeter, 1942, p. 83). Given systemic uncertainty, knowledge non-rivalry, sunk costs of entry and innovation, and structural heterogeneity, creative destruction certainly appears to be the proper benchmark of a competitive economy. In other words, an economy characterized by innovation and entrepreneurship encouraged by (quasi) monopoly rents and large-scale growth, innovation-based market selection, temporary dominant positions, and technical progress that benefits from the creation of new technologies and the destruction of obsolete ones. Using a large longitudinal dataset covering the population of Portuguese firms from 1986 to 2018, this research has investigated the long-term stability of this process responsible for promoting technical progress, reducing prices and increasing real wages. Moreover, examining the main industrial dynamics trends has further enabled disentangling the debate around the determinants of the productivity slowdown that most developed economies have suffered during the new century.

In new neoclassical endogenous growth theories, reallocation efficiency is only hampered by positive knowledge externalities, which induce underinvestment in R&D and, therefore, insufficient jobs for highly skilled workers (Acemoglu et al., 2018). Here, creative destruction is sustainable as long as there is (public or private) investment in knowledge and flexible markets—especially labour and product markets (Aghion & Akcigit, 2019). In firm dynamics models of evolutionary tradition, although entry and survival are more stringent in the industry's mature phase, turbulence (as far as market shares are concerned) is expected to be persistent (Winter et al., 2000; 2003). The economy-wide reallocation and turbulence will also be continuously fuelled by new markets and production methods.

These theoretical approaches are based on a causal relationship between innovation and industry structure, while current and potential competition are expected to limit dominant firms' market power. Thus, the long-term dynamic properties depend critically on a permanent inflow of entrants capable of using technologies developed within or outside the industry to displace *sluggish* monopolies. Acemoglu et al. (2018) claim that firms have a greater propensity to innovate and grow when young. This conjecture has been confirmed by Alon et al. (2018), who found a downward-sloping relationship between business age and productivity. Decker et al. (2014) have also argued that high-growth start-ups are responsible for offsetting losses resulting from the premature death of other firms in their cohort. Still, according to Aghion et al. (2009), high-productivity surviving entrants play a crucial role in stimulating frontier incumbents' innovation (the escape-competition effect).

The evolutionary perspective warns that innovation opportunities are ultimately constrained by the prevailing technological paradigm (Dosi & Nelson, 2010; Perez, 2010).[78] When the knowledge base has been virtually exhausted, inventiveness dries out, the return on innovation diminishes, business dynamism slows down, and markets most likely concentrate sales on companies with the leading technology. However, as happened with the fall of the electricity or the internal combustion engine paradigms, a new innovation wave is expected to emerge, reviving creative destruction and shaking up the established order.

Hence, the Schumpeterian view seems to conceive that accumulation is always the result of wealth creation. Nevertheless, we have argued that market selection discipline may be circumvented from a certain accumulation level (regarding technology, capital and finance), particularly in the declining phase of a given paradigm. At such a point, a non-Schumpeterian selection or predominance of non-Schumpeterian rents is likely to arise.

The Portuguese industrial dynamics in the late 20th century and, primarily, that of the markets that emerged with the technological paradigm (or 'Kondratieff' long wave) of ICT, support the Schumpeterian theses of competition, innovation and technical progress. As shown in *Chapter 5*, the entry and contribution of new market players were vigorous up to 2000, with an increasing job reallocation and a positive trend favouring job creation. This dynamism led to increased dispersion of the growth rate distribution, driven mainly by a higher 90-50 percentile differential and hence an increasing share of high-growth firms (HGF). Confirming theoretical predictions, high-growth *young* firms seem to have offset losses related to the early death of the other firms in their cohort, such that the employment share of young enterprises remained constant. The upsurge in these business dynamism indicators was more pronounced in the knowledge-intensive activities (KIA), revealing the dominant role of industries that directly incorporated the new driving technological paradigm in aggregate performance. Indeed, the share in total employment of new and young firms exhibited a growing trend in this sector.[79]

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[78] Dosi's (Dosi, 1982) technological paradigms resemble long waves, or "Kondratieff" waves, of Schumpeter (Schumpeter, 1939), which tell how radical innovations shape the long-term cyclical evolution of capitalism.

[79] Table D.1 in Appendix summarises the main findings of the thesis, showing two major breakdowns, each reflecting distinct patterns of industrial dynamics in terms of time and sectorial knowledge intensity.

For its part, *Chapter 6* shows that sales concentration remained relatively constant during the 1900s, even though the economy-wide market share instability decreased and leadership persistence increased. Yet, this was not the case in KIA industries, where sales accumulation and leadership persistence exhibited downward trends. Furthermore, since imitation and selection processes occurred faster than innovation, the economy-wide technological gap between leaders and followers diminished, particularly in traditional sectors. In fact, the innovative gap showed a decreasing pattern in these industries. However, the technology gap significantly widened in the KIA sector due to a persistent innovation gap between leaders and followers. Finally, although data regarding the share of zombie firms in the pre-2000 era is unavailable, the results in *Chapter 7* suggest it was relatively low at the beginning of the new century.

The late 20th century was, therefore, characterised by intense creative destruction, impelled critically by the rise of knowledge-intensive activities. During the pre-2000 interval, the economy experienced high business dynamism—in terms of reallocation and turbulence, the contribution of new and young firms, and incidence of high-growth companies—, enhanced innovation and knowledge diffusion, and lower market concentration and entrenchment probability of industrial leaders. In other words, the technological shock linked to ICT, and the necessary alteration of production trajectories, gave new firms renovated impetus to compete for technical and market dominance, even in traditional sectors.

Nevertheless, industrial dynamics suffered a structural decline in the 21st century. The results of *Chapter 5* indicate, in particular, that the entry of new enterprises and the corresponding share in total employment have exhibited a secular decreasing trend. As a result, both (net) firm and job creation rates by entrants have become negative, even in the KIA sector. Moreover, the reallocation rate and the dispersion of the growth rate distribution declined markedly. The decline in dispersion was more pronounced in the KIA sector, with a significant reduction in the 90-50 differential and, ergo, a lower prevalence of HGF. Although the dynamism of young firms has been notable, with increasing growth rates, especially in the 90th percentile, it has not offset the overall lower entry and survival rates. Nor is it observed that the higher performance of infant companies has impacted mature firms, whose rates have instead been clustered at the median. Still, high-growth young firms in the KIA sector have exhibited a declining growth pattern since 2000. As a result, new and young companies have seen a decline in their aggregate employment share and net job creation, especially in the KIA industries.

Chapter 6 also shows that lower firm dynamism, debilitated potential competition, and industrial ageing also manifested in a higher concentration rate, a greater chance of preserving dominant positions and a decreased market share instability. The technology gap between leaders and followers has widened as well, while the innovation gap has almost vanished, implying that industry leaders have been able to expand their market share and preserve their dominant positions with diminishing innovative efforts. Moreover, a more significant technological gap in a scenario of slow technical change (and lower leaders' innovation) suggests that knowledge diffusion has been hampered and resources have been inefficiently reallocated. The increase in concentration and leadership persistence and the stabilisation of market shares were more pronounced in the knowledge-intensive industries. That is, trends are opposite to those observed in the late 20th century. Nonetheless, note that a wider technological gap and a narrower innovation gap were specific to the more traditional sectors (i.e., Non-KIA). In the KIA sector, in turn, the decrease in the innovation gap was accompanied by a reduction in the productivity gap. In any event, the leading firms in both sectors, KIA and Non-KIA, increased their market share and entrenchment likelihood with smaller innovative efforts. Finally, according to Chapter 7, it is found that the weakening of both the business dynamism and competitive regime has taken place along with a higher incidence of unprofitable and highly indebted firms (i.e., zombies), particularly during the financial crisis (possibly due to a higher creditor forbearance).

In short, after intense creative destruction, the Portuguese economy seems to have suffered a profound deterioration in industrial dynamism. This weak economic performance is threefold: a decline in the rates of entry, turbulence, reallocation, and business growth; increased market concentration, leadership persistence and zombie incidence; and a larger (smaller) technological (innovation) gap between leaders and followers.

The empirical literature has also reported an across-the-board slowdown in creative destruction in the 2000s. However, it is here where interpretative differences emerge most visibly. In particular, Covarrubias et al. (2020) suggest that the decline of the new-century industrial dynamics may be explained by two types of concentration: *good* and *bad*. The *good* concentration (i.e., Schumpeterian concentration) hypotheses argue that a higher cross-elasticity of substitution (the α parameter in Aghion et al.'s (2001) model) and greater use of intangible capital favour a reallocation of sales towards the most efficient producers, increasing concentration and productivity but discouraging innovation from potential competitors in the long-run (Aghion, Bergeaud, et al., 2022a; Autor et al., 2017). On the other hand, the *bad* concentration (i.e., non-Schumpeterian concentration) theories claim that a growing prevalence of (structural, behavioural, and institutional) barriers to competition weakens technical progress while facilitating the concentration of sales and profits towards dominant rent-seeking firms (De Loecker et al., 2020; Lambert, 2019; Philippon, 2019; Stiglitz, 2019).

According to Covarrubias et al.'s (2020) model, if good concentration hypotheses account for long-term patterns, increased concentration and profits are expected to be accompanied by higher investment and productivity from surviving firms and greater market share instability, leadership turnover, and exit hazard. However, if barriers to competition explain the phenomenon, increases in concentration and profit margins should go along with a decline in productivity, entry and exit rates, market instability, leadership turnover and investment. In *Chapter 3*, we additionally proposed that the type of concentration is mediated by the degree of exploitation of the technological paradigm (the ICT revolution, in this case) in such a way that creative destruction is expected to dominate in the ascending phase of the innovation wave. However, the opposite is likely to have occurred in the descending phase, when the paradigm loses its creative potential. On the whole, we have argued that productivity slowdown is an increasing function of non-Schumpeterian market selection.

Our analysis therefore suggests that the Portuguese industrial dynamics evolved from a *Schumpeterian* to a *non-Schumpeterian concentration* in the last forty years. Specifically, we observed intense creative destruction up to 2000, with high job reallocation, new and young firms' contribution, the incidence of HGF, market instability, leadership turnover, productivity growth, and a constant or decreasing concentration, especially in knowledge-intensive sectors. This pattern was reversed by the start of the new century, with a rise in non-Schumpeterian concentration. The joint trajectory of the technological and innovation gaps supports this presumption. The observed secular reduction of the innovation gap between leaders and followers should have resulted in a narrow technology gap unless there were barriers to competition, including the hindrance of knowledge flow. Still, leaders have expanded their dominant positions with lower innovative efforts, reaching a zero relative innovation gap relative to followers by 2018. This profile fully characterises a non-Schumpeterian concentration. Yet, this is not entirely the case in the knowledge-intensive activities sector, where the innovation gap closing went along with a productivity gap reduction. In other words, as expected in a scenario of slowed technological change, selection and imitation seem to have prevailed over innovation. Nevertheless, we cannot assume a *good* concentration in this sector either, because industry leaders have enjoyed greater entrenchment possibilities and have increased their sales share by relying less on productivity gains, while market instability and business dynamism have seriously weakened (especially all in new and young companies).

Confirming our expectations, *Chapter 6* found that *bad concentration* can possibly be due to *good concentration*. This finding entails a profound dilemma (which I called the "paradox of Schumpeterian competition") since *competition tends to Schumpeterian concentration, and then concentration weakens competition*. Accordingly, industry-level regressions indicate that leaders preserve their dominant positions more easily in markets with a higher concentration rate. At the same time, the greater the leadership persistence, the lower the market share instability. The results also show that dominant firms have diminished incentives to innovate in deteriorated competitive settings (that is, with weak market instability and high concentration). Fixed effects panel regressions indicate as well that the higher the industrial concentration, the smaller the effect of firm productivity growth on market share expansion (i.e., the central Schumpeterian competition outcome).

A non-Schumpeterian selection at the exit margin, and the resulting zombie survival, have also undermined industry productivity due to inefficient reallocation and negative externalities, as shown in *Chapter 7*. The findings indicate that zombie firms are less productive than non-zombies and that industry productivity growth deteriorates with the share of zombies. Furthermore, multinomial logistic regressions suggest that, conditional on constant relative productivity, small firms with financial distress are more prone to liquidation than their larger counterparts, and the likelihood of zombie survival increases with firm size. Hence, a higher market share also enables circumventing selection forces at the exit margin. The findings additionally indicate that not all zombies are unviable firms. Therefore, barriers hindering their restructuring also play a crucial role. If all zombies were unprofitable, then quick and easy liquidations should likely be the right way out. However, as many are financially distressed, a creditor-centred regime may favour less productive but deep-pockets agents. Indeed, the debtor-friendly Portuguese insolvency reforms of 2012 were proven effective in reducing zombie survival and its adverse effect on reallocation. In particular, the findings show that a well-designed institutional framework can increase the transition probability into reorganisation and recovery of those more productive zombies.

The hypotheses of good concentration anchored to higher demand-side competition and intangible capital deepening seem therefore to explain the pre-2000 trends but not the new-century Portuguese industrial dynamics. Instead, the results support the view that increased barriers to competition (including exit barriers) have undermined creative destruction, thus endorsing the *bad* concentration theories and one of our key propositions, that productivity stagnation is an increasing function of non-Schumpeterian market selection, particularly of non-Schumpeterian concentration and exit selection.

It is important to emphasise that trends in knowledge-intensive industries differed markedly from their counterparts in traditional sectors, mainly during the 1980s and the 1900s. These findings support Schumpeter's theory of capitalist evolution and its long-term cycles based on the rise and fall of radical innovations, which ultimately shape production processes and market relations. Indeed, the vigorous industrial dynamics of knowledge-intensive (or high-tech) sectors in the 1980s and the 1990s are not unique to the Portuguese economy. For example, Haltiwanger et al. (Haltiwanger et al., 2014), Decker et al. (2016), and Bijnens and Konings (2020) reported increasing patterns of young firms' contribution and job reallocation in high-tech sectors in the late 20th century in the US and Belgium. Trends that differed widely from their counterparts in traditional industries. On the other hand, the rise of non-Schumpeterian selection seems to coincide with the decline of the ICT technological paradigm. That is, when the expected return to innovation is lower, the incentives to evade market selection appear to be higher.

Is creative destruction sustainable in the long term, as suggested by Schumpeter? The technologically stagnant, more concentrated, and less dynamic industries characterising Portuguese and most advanced economies during the new century appear to indicate the opposite. The intense creative destruction triggered by the emergence of the ICT technological paradigm seems to support Schumpeter's claims. Indeed, the technological shock linked to the ICT revolution "set and kept the capitalist engine in motion" for almost two decades. Nevertheless, business dynamism has been undermined in the long run. Notwithstanding the better performance of young firms, this seems to be the case in the Portuguese economy. Certainly, the battle among *old corporate giants* might still fuel competitive forces, but, as Robinson (1962) argued, they cannot be relied upon to maintain the continued pressure that constant innovation and job creation require.

Regarding public policy, considering that creative destruction has weakened, the institutional agenda becomes central to ensuring that technological change and value-based distribution keep afloat. However, given the heterogeneity in production and Schumpeterian competition, the traditional (universal) Keynesian policies and the corresponding type of

Welfare State appear to be ineffective tools for achieving these goals. To protect the public good of competition, as the engine of capitalism and its regulatory device, it is therefore mandatory to design screening mechanisms that guarantee an efficient allocation of social resources (avoiding, for example, zombie survival).

In this context, a competition policy should be rethought, restricting old and new anti-competitive practices such as pre-emptive mergers and acquisitions and predatory behaviour or price discrimination by exploiting Big Data. It is also important to assess whether higher tax rates for companies that have accumulated non-Schumpeterian rents over a long time are appropriate for reducing perverse incentives. In a world with non-Schumpeterian rents, there should not be a trade-off between efficiency and equality.

Moreover, stimulating transformative entrepreneurship is the proper way to preserve competition and foster technical progress in a creative destruction framework. This fact requires democratising access to financing and technology to encourage learning and innovative processes, especially in young, financially constrained firms. In light of the direct relationships between risk and technological novelty and between risk and credit rationing, it is also necessary to create specific public and private instruments to facilitate access to innovation funding (e.g., providing seed and risk capital). Finally, although intellectual property ought to preserve innovation incentives, current patent regimes are likely to offer excessive protection that ends up slowing the innovation process (by reducing the knowledge base) and favouring the entrenchment of monopolies. Weaker and better-designed regimes—including patent pools, compulsory licenses, and shortened patent life—might effectively restore competition and technological change. The question remains, however, whether the codified nature of knowledge—and the resulting imitation cost—already provides the monopolistic time required to recover the sunk costs of innovation.

Other issues are still open for future research. On the one hand, although a market share expansion with declined innovation efforts suggests an increase in product market rents (and, likely, a lower labour share), it is worth asking whether non-Schumpeterian concentration in tandem with task mechanisation and job polarisation affects wage determination. On the other hand, considering that technological paradigms (taken as the technology of technical progress) tend to yield decreasing returns once their potential has been exhausted, it is striking that the rise of non-Schumpeterian concentration and the slowdown of business dynamism have coincided with the decline of the ICT technological paradigm. History tells us that a new wave of radical innovation will eventually emerge, reactivating productivity growth and industrial dynamics. Nonetheless, between the fall of one paradigm and the rise of its successor, several creative destruction properties seem to lose prevalence, giving rise to non-Schumpeterian concentration and possibly zombie survival, for instance. It is therefore crucial to investigate whether the dynamics of value extraction (through barriers to competition, for example) are directly related to a higher opportunity cost to continuing innovating. Likewise, may the seeking and accruing non-Schumpeterian rents delay the emergence of a new paradigm and limit its potential disruptive ability?

This thesis argues that over the last forty years, with an institutional context favourable for the big company, much of the boom and fall of Portuguese industrial dynamics was driven by the rise and decline of the ICT technological paradigm. In the process, there has been an income accumulation and a business survival not entirely in tandem with productive or innovative efforts. That is, while we wait for the arrival of a new paradigm, value extraction seems to take the central stage. Paraphrasing the Italian philosopher Gramsci, it seems that, *while the obsolete is destroyed and the new takes to be created, between light and shadow, predators spread*. The revival of competition and technical progress—in a framework of equal opportunities, efficiency, and sustainability—therefore requires a collective effort favouring value creation and sanctioning its extraction. Future research should address these issues head-on.

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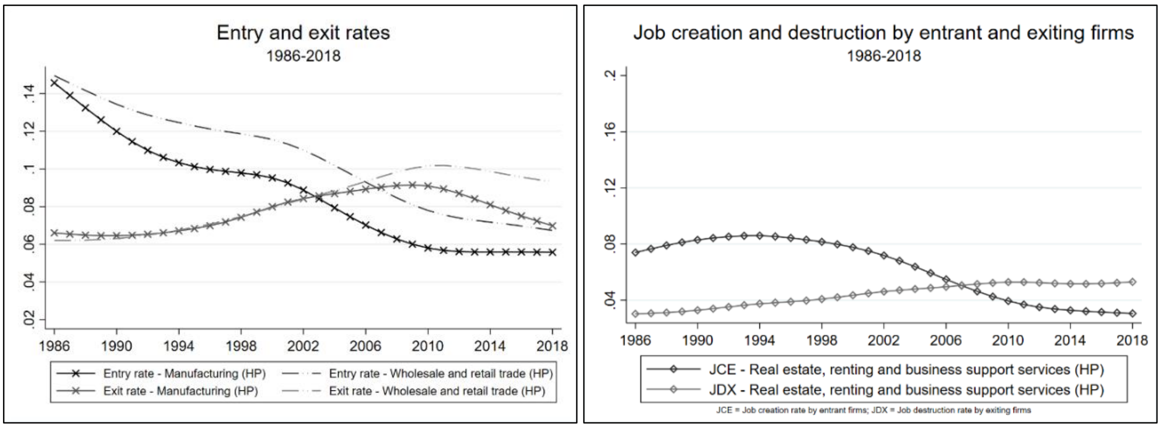
Appendix A

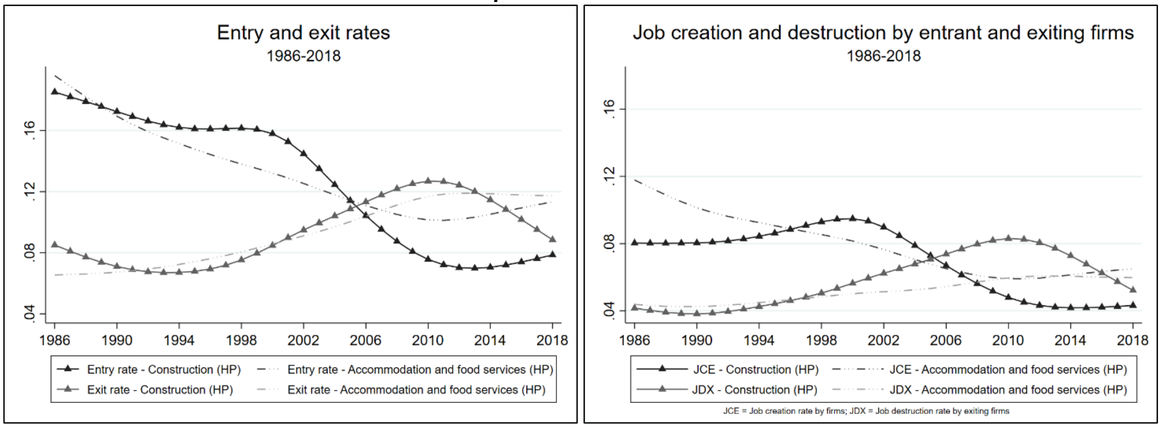
Figures to complement Chapter 5

Figure A.1 The share of entering and exiting firms in the Manufacturing and Wholesale and retail trade sectors, 1986-2018



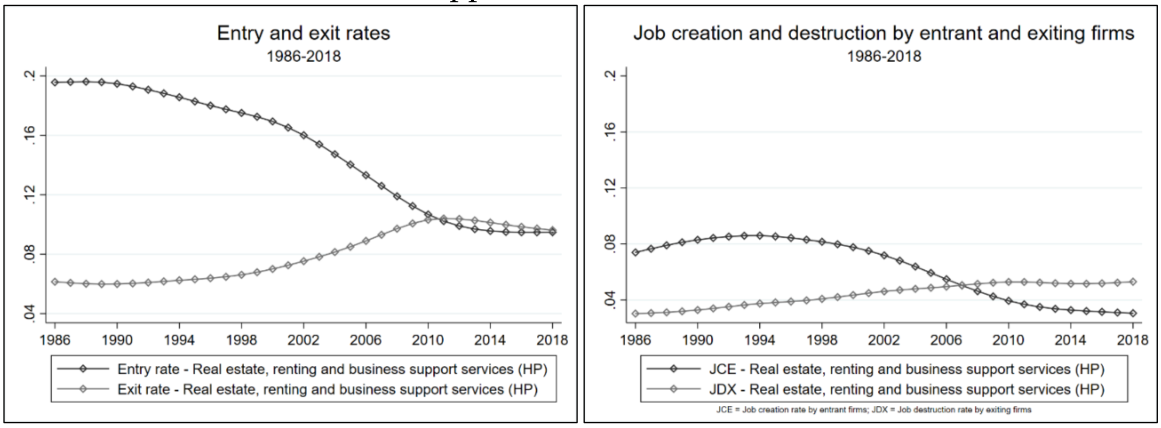
Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms) by each sector. The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms by each sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.2 The share of entering and exiting firms in the Construction and Accommodation and food services sectors, 1986-2018



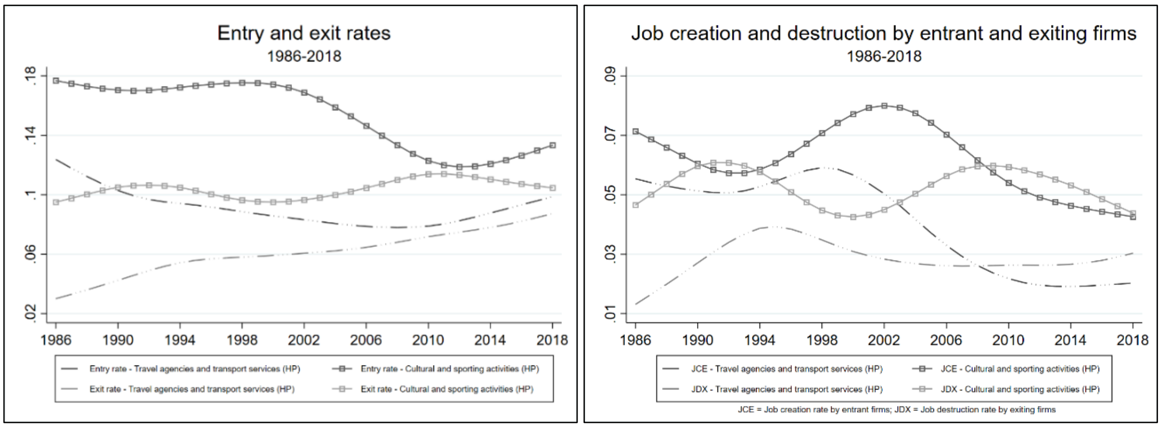
Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms) by each sector. The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms by each sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.3 The share of entering and exiting firms in the Real estate, renting and business support services sector, 1986-2018



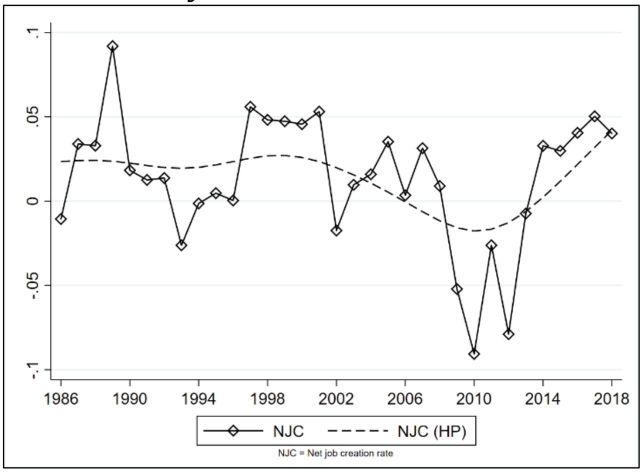
Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms) by each sector. The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms by each sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.4 The share of entering and exiting firms in the Travel agencies and transport-related services and Recreational, cultural and sporting activities subsectors, 1986-2018



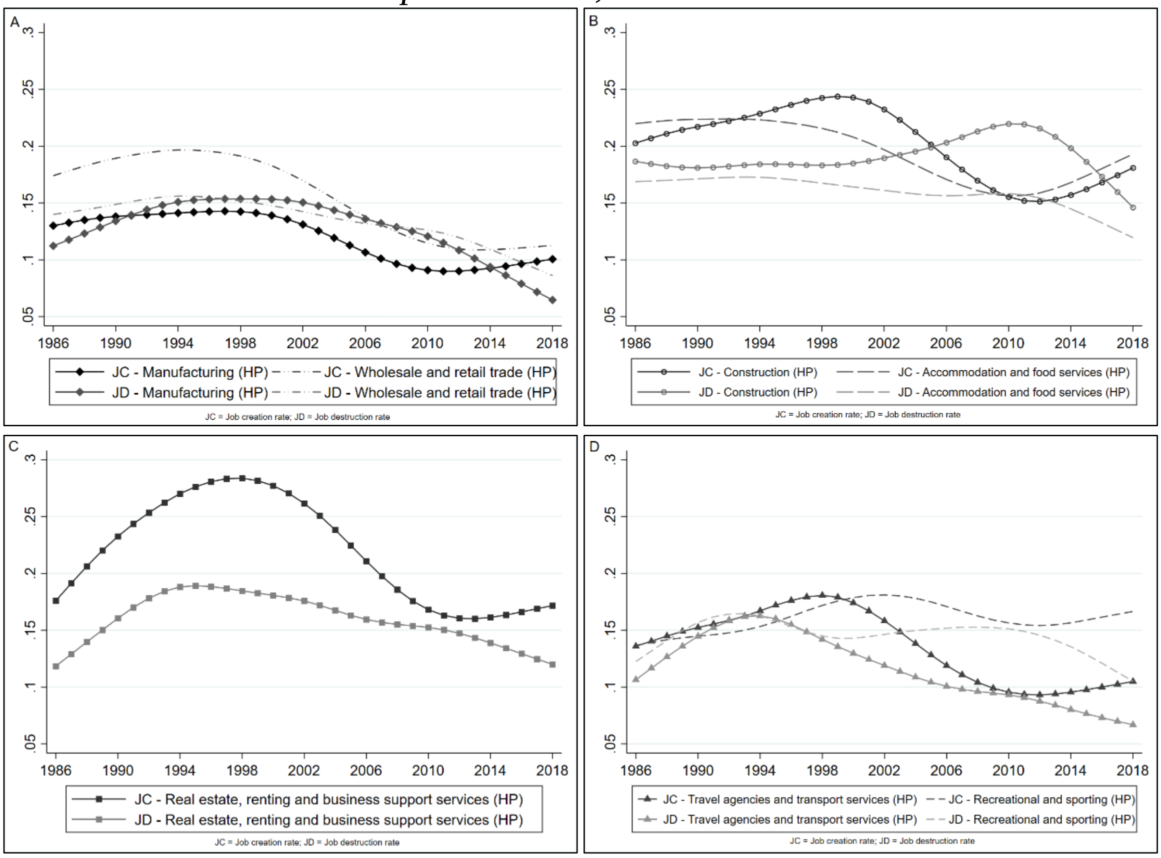
Note: The entry (exit) rate is defined as the ratio between entering (exiting) firms and the total number of enterprises in "t" (i.e., entering, continuing and exiting firms) by each sector. The job creation (destruction) rate by entrant (exiting) firms is computed as the employment-weighted average of the employment-growth rates of entrant (exiting) firms by each sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.5 The economy-wide Net Job Creation rate, 1986-2018



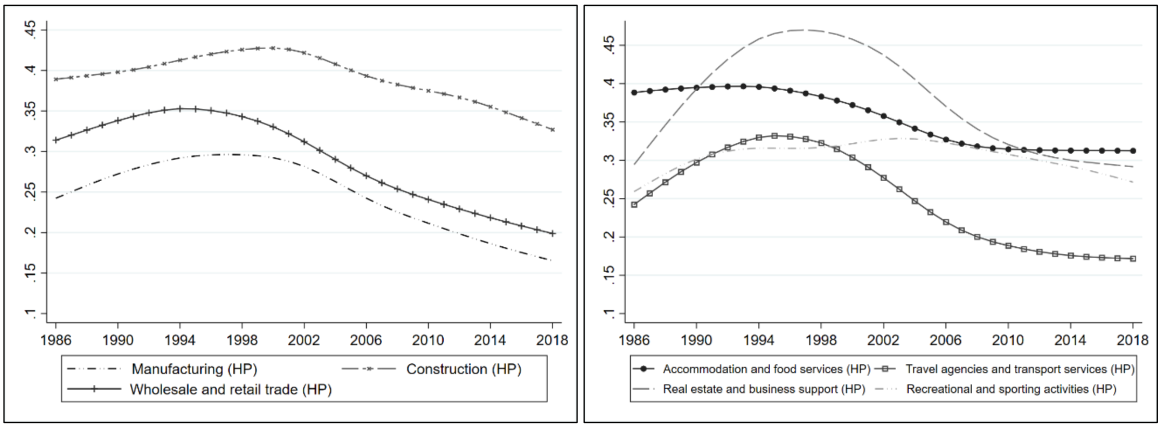
Note: The net job creation rate is computed as the employment-weighted average of the employment-growth rates of all firms (i.e., continuing, entering and exiting firms). Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100.

Figure A.6 Job Creation and Destruction rates by sector of economic specialisation, 1986-2018



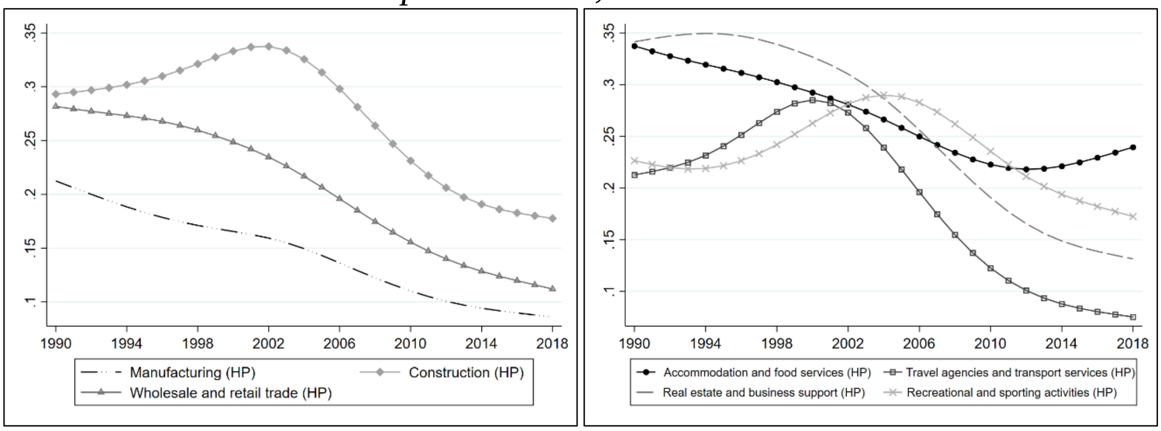
Note: The job creation (destruction) rate is computed as the employment-weighted average of the absolute value of employment-growth rates of all firms with non-negative (negative) growth rates, by sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.7 Job Reallocation Rate by sector of economic specialisation, 1986-2018



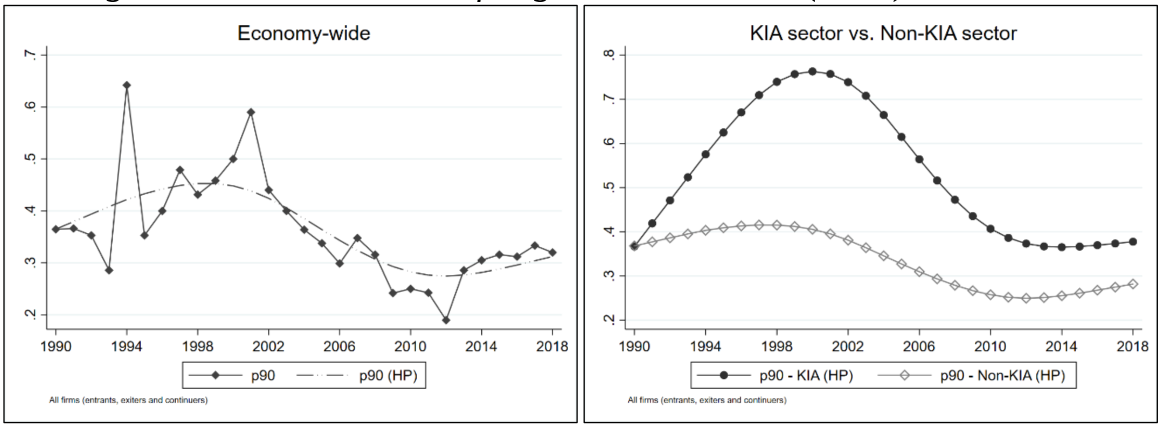
Note: The job reallocation rate is equal to the sum of the rates of job creation and job destruction, by sector. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.8 The employment-share of young firms by sector of economic specialisation, 1990-2018



Note: The share of employment at young firms is calculated as the ratio of total (average) employment in young companies to total (average) employment in all firms, by sector. Young firms are less than 5 years old. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure A.9 The evolution of High-Growth Firms (HGF), 1990-2018



Note: The typical performance of a high-growth firm (HGF) is observed by estimating the 90th percentile growth rate. The 90th percentile is based on the employment-weighted distribution of employment growth rates for all firms, across the economy (left panel) and by sector (right panel). Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Knowledge-intensive activities (KIA) are classified by using the methodology developed by the Statistical Office of the European Union (Eurostat). Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

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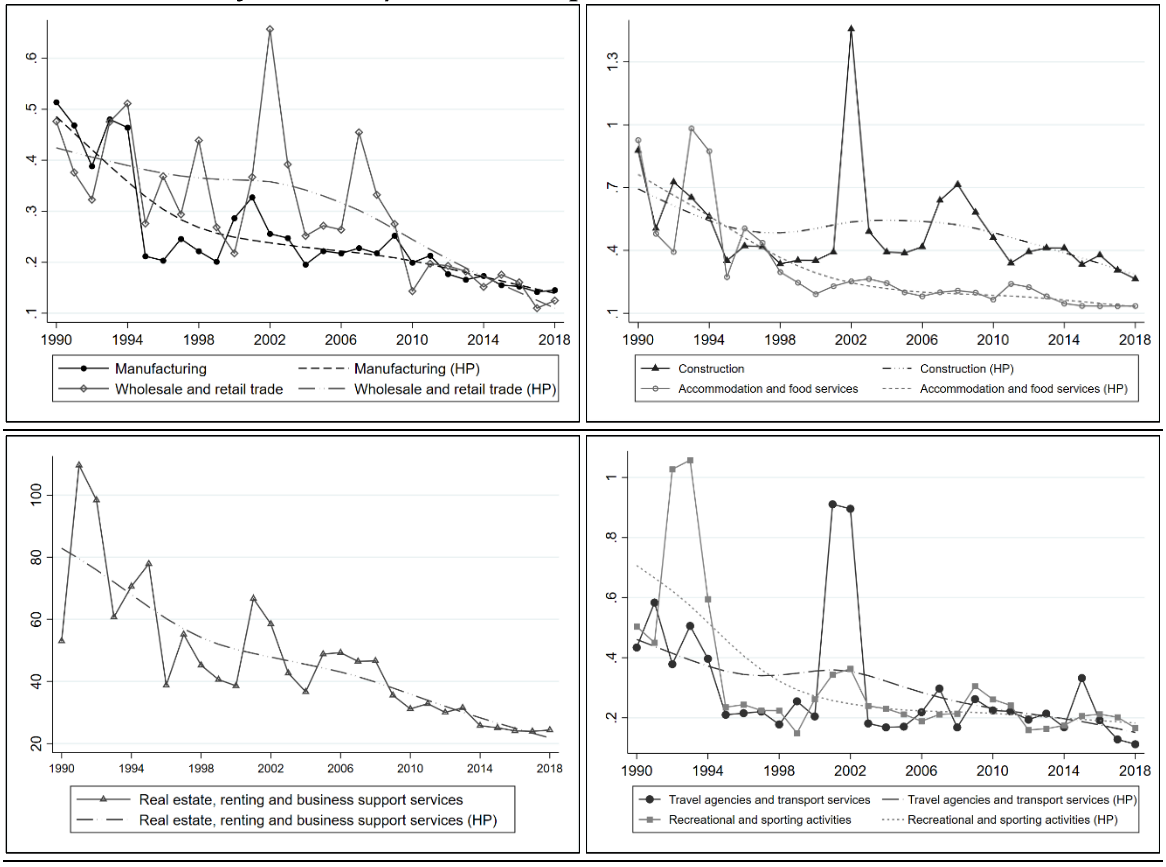
Appendix B

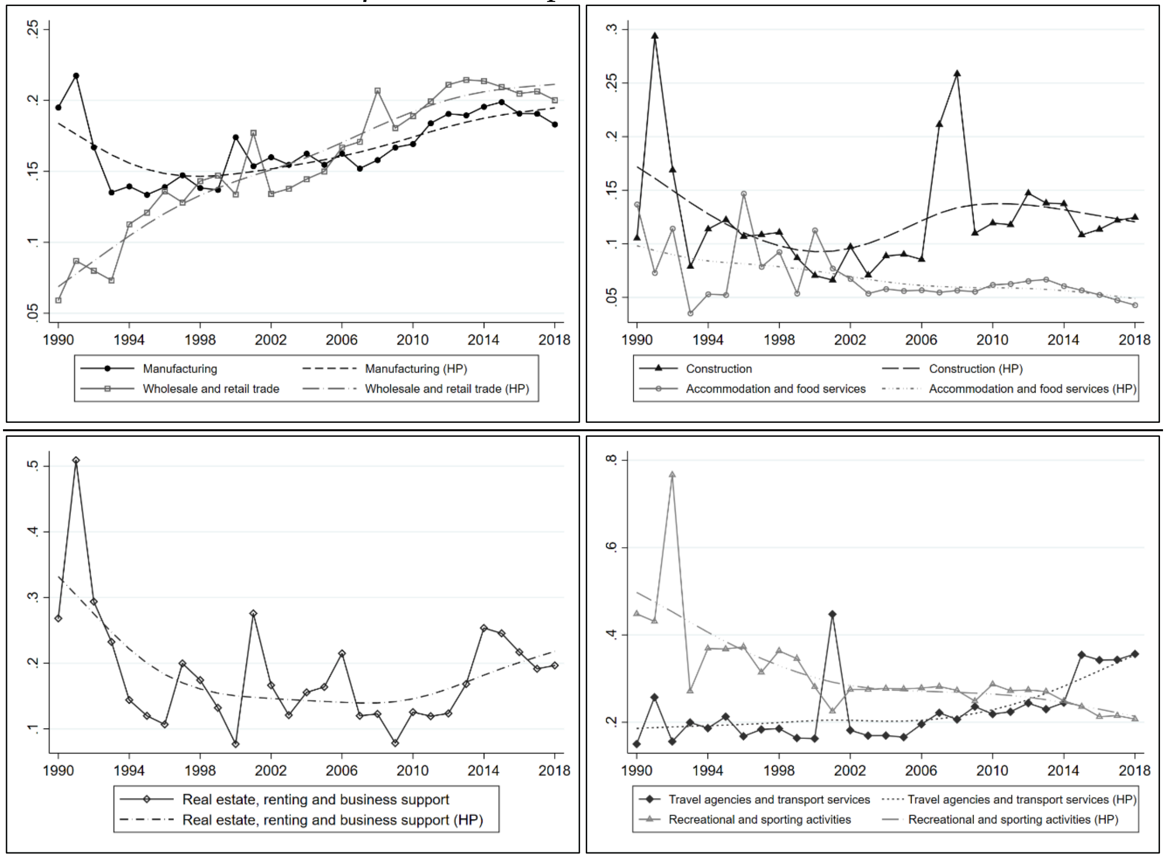
Figures to complement Chapter 6

Figure B.1 The average market share instability across two-digit industries by sector of economic specialisation, 1990-2018



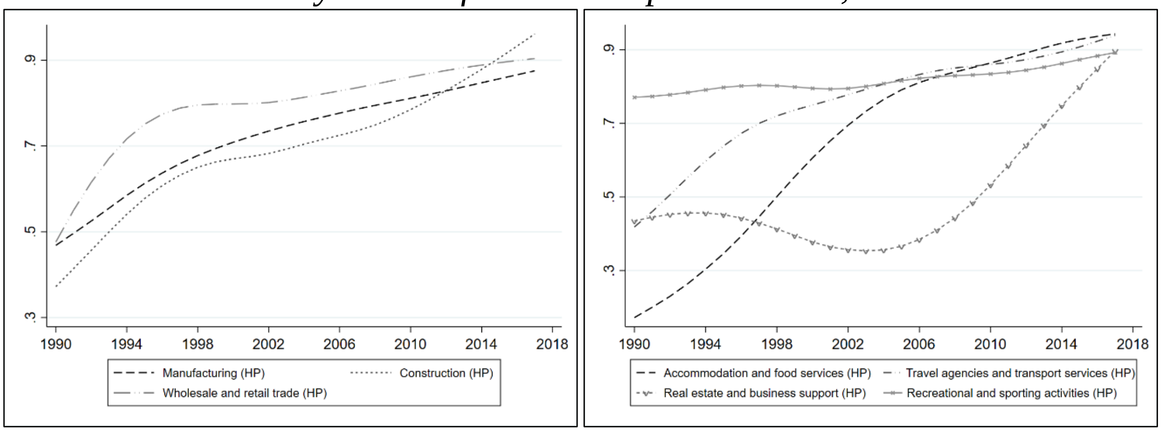
Note: The 'market share instability index' measures the summation of the absolute change in market shares in each year. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure B.2 The average C5 concentration index across two-digit industries by sector of economic specialisation, 1990-2018



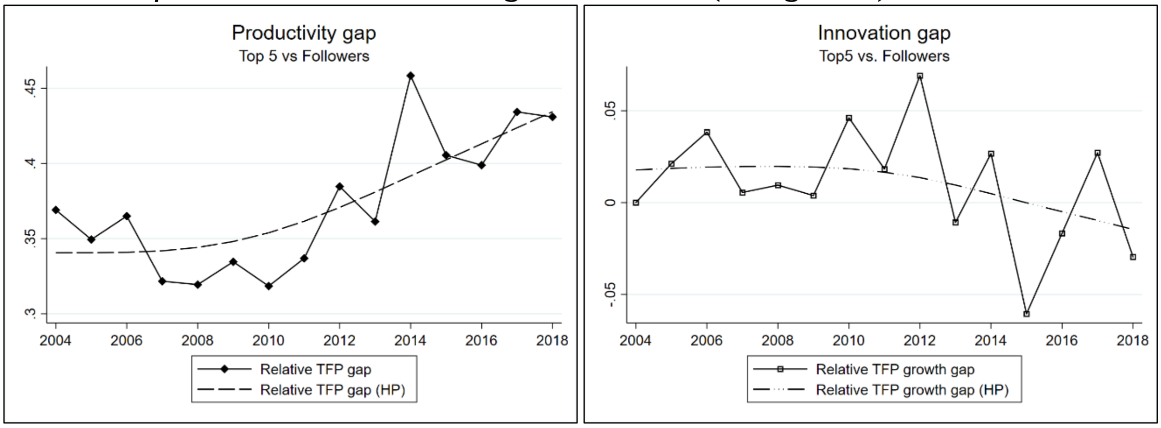
Note: The C5 concentration index denotes the share of sales at the 5 largest firms in the industry. To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is calculated the weighted average across all industries. The weighting factor is the number of firms in each industry. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure B.3 The average leadership persistence rate across two-digit industries by sector of economic specialisation, 1990-2017



Note: The leadership persistence rate is defined as the ratio of market share leaders in "t" remaining in the leadership in t+1 to the total number of leading firms in "t". To aggregate values, the industry indicator is calculated for each 2-digit industry and then it is computed the weighted average across all industries by major sector. The weighting factor is the number of firms in each 2-digit industry. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

Figure B.4 The average productivity and innovative gaps between leaders and followers across two-digit industries (using TFP), 2004-2018



Note: The relative productivity gap corresponds to the difference between the average relative productivity of the five market share leaders and that of the followers in a typical 2-digit industry. The innovation gap corresponds to the difference between the average relative productivity growth of the five market share leaders and that of the followers. The productivity growth is computed as log differences and as a deviation from industry-mean efficiency growth. The selected efficiency measure is Total Factor Productivity (TFP). Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Industries are defined on a time-consistent CAE Rev.2 basis. Y axis does not start at zero.

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Appendix C

Tables to complement Chapter 7

Table C.1 Post-matching test for covariate balance over treatment levels of treated zombies

Predictor	One match				Two matches			
	Standardised differences		Variance ratio		Standardised differences		Variance ratio	
	Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
TFP	-0,0791	-0,028	1,2446	1,1116	-0,0791	-0,0321	1,2446	1,1342
Capital	-0,3738	-0,0382	1,0036	1,0986	-0,3738	-0,042	1,0036	1,1151
Labour	-0,286	-0,0532	0,9093	1,116	-0,286	-0,0618	0,9093	1,1437
Leverage	0,427	0,0731	1,5951	1,0881	0,427	0,08	1,5951	1,1013
Age	0,6855	0,1553	1,4747	1,0978	0,6855	0,1688	1,4747	1,1052
EBITDA	-0,4442	-0,0022	0,2991	0,9817	-0,4442	-0,0022	0,2991	0,9796
Zombie duration	0,5271	0,1495	1,323	1,3085	0,5271	0,1575	1,323	1,3143
Business cycle	0,5351	0,0642	0,4	0,7531	0,5351	0,0679	0,4	0,7439
Industry dummy:								
Construction	-0,1543	0	0,7462	1	-0,1543	0	0,7462	1
Trade	-0,0508	0	0,9651	1	-0,0508	0	0,9651	1
Accommodation	0,3092	0	1,591	1	0,3092	0	1,591	1
Real estate	-0,0476	0	0,7778	1	-0,0476	0	0,7778	1
Business services	0,0001	0	1,0002	1	0,0001	0	1,0002	1
Location dummy:								
Algarve	-0,0114	0	0,9565	1	-0,0114	0	0,9565	1
Central Region	-0,0112	0	0,982	1	-0,0112	0	0,982	1
Lisbon	0,012	0	1,0084	1	0,012	0	1,0084	1
Alentejo	0,0105	0	1,0443	1	0,0105	0	1,0443	1
Açores	0,0408	0	1,4938	1	0,0408	0	1,4938	1
Madeira	0,0119	0	1,0678	1	0,0119	0	1,0678	1

Notes: The table shows the standardised differences and variance ratios of the outcome variable predictors for the raw data and the matched sample (with one and two matches). The binary outcome variable takes the value of one if the company leaves the zombie status in $t+1$ (i.e., recovers or exits the market) and zero otherwise (i.e., zombie entrenchment). The matrix of predictors contains TFP (as deviation from the industry mean), capital, labour (employment), leverage, EBITDA (as a cash-flow proxy), and firm age (all in logs), as well as business cycle measure (the annual growth rate of GDP in each region - NUTS II), and industry and location dummies. The similarity is computed by the Mahalanobis distance metric. The Abadie and Imbens' (2011) approach is used to correct the large-sample bias. It is imposed exact matching on industry affiliation and location.

Table C.2 Effects on recovery and exit probabilities, Multinomial logistic regression

Variables	Recovery			Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
IR		0.5774***	1.3884***		0.1999***	–0.5092***
		(0.0157)	(0.1302)		(0.0174)	(0.1653)
TFP	0.3953***	0.4072***	0.3681***	–0.5719***	–0.5695***	–0.6503***
	(0.0135)	(0.0135)	(0.0174)	(0.0094)	(0.0094)	(0.0119)
TFP × IR			0.0741***			0.2177***
			(0.0253)			(0.0181)
Capital	0.0023	0.0090	0.0363***	–0.1428***	–0.1414***	–0.1678***
	(0.0063)	(0.0062)	(0.0074)	(0.0072)	(0.0072)	(0.0085)
Capital × IR			–0.0659***			0.0935***
			(0.0112)			(0.0139)
Labour	0.0431***	0.0651***	0.0319***	–0.1409***	–0.1321***	–0.1108***
	(0.0094)	(0.0094)	(0.0113)	(0.0106)	(0.0107)	(0.0127)
Labour × IR			0.0789***			–0.0646***
			(0.0169)			(0.0221)
Leverage	–0.3138***	–0.3429***	–0.2506***	0.4533***	0.4447***	0.5292***
	(0.0139)	(0.0140)	(0.0192)	(0.0133)	(0.0133)	(0.0163)
Leverage × IR			–0.1909***			–0.1789***
			(0.0240)			(0.0233)
Observations	198,104	198,104	198,104	198,104	198,104	198,104

Note: The base category for the dependent variable is the continuing zombie status. TFP, Capital, Labour and Leverage are in logs. IR is a dummy for the post-reforms zombies. Unreported are estimates of control variables including log of EBITDA (as proxy of cash-flow), log of age, log of zombie duration, business cycle measure (GDP-growth rate by region), and industry and location dummies. The variables were winsorized at the 1st and 99th percentiles. Firm-cluster robust standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table C.3 Effects on recovery and exit probabilities, Multinomial logistic regression - Robustness check using Labour Productivity

Variables	Recovery			Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
IR		0.5805***	1.6516***		0.1972***	-0.4529***
		(0.0157)	(0.1267)		(0.0171)	(0.1550)
Labour productivity	0.0791***	0.0822***	0.0719***	–0.1314***	–0.1307***	–0.1513***
	(0.0027)	(0.0027)	(0.0037)	(0.0021)	(0.0021)	(0.0026)
Labour productivity ×			0.0207***			0.0577***
			(0.0051)			(0.0040)
Capital	–	–0.0202***	0.0158**	–0.0926***	–0.0910***	–0.1180***
	(0.0061)	(0.0061)	(0.0073)	(0.0067)	(0.0067)	(0.0078)
Capital × IR			–0.0852***			0.0975***
			(0.0108)			(0.0129)
Labour	0.0107	0.0320***	–0.0015	–0.1129***	–0.1048***	–0.0722***
	(0.0097)	(0.0097)	(0.0117)	(0.0105)	(0.0105)	(0.0124)
Labour × IR			0.0792***			–0.1001***
			(0.0174)			(0.0217)
Leverage	–	–0.2791***	–0.1899***	0.3470***	0.3395***	0.3977***
	(0.0143)	(0.0144)	(0.0198)	(0.0128)	(0.0128)	(0.0157)
Leverage × IR			–0.1882***			–0.1065***
			(0.0247)			(0.0228)
Observations	198,104	198,104	198,104	198,104	198,104	198,104

Notes: The base category for the dependent variable is the continuing zombie status. Labour productivity, Capital, Labour and Leverage are in logs. IR is a dummy for the post-reforms zombies. Unreported are estimates of control variables including log of EBITDA (as proxy of cash-flow), log of age, log of zombie duration, business cycle measure (GDP-growth rate by region), and industry and location dummies. The variables were winsorized at the 1st and 99th percentiles. Firm-cluster robust standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table C.4 Expected probabilities, Average marginal effects and (average) differences-in-differences between pre- and post-reforms periods - Robustness Check comparing effects by industrial turbulence

Covariate	Transition	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Pairwise comparison (Post minus Pre-reforms)
High turbulence industries					
A. Expected probabilities: $\Pr(Y_{i,t+1} = j)$					
	Remain as zombie	0.7142***	0.7361***	0.6512***	-0.0849***
	Recovery	0.1266 ***	0.1058***	0.1702***	0.0644***
	Exit	0.1592***	0.1580***	0.1785***	0.0205***
B. Average marginal effects (AME): $\partial p_j / \partial \kappa_k$					
TFP	Remain as zombie	0.0215***	0.0398***	-0.0154***	-0.0552***
	Recovery	0.0480***	0.0374***	0.0717***	0.0343***
	Exit	-0.0696***	-0.0772***	-0.0563***	0.0208***
Capital	Remain as zombie	0.0207***	0.0204***	0.0208***	0.0004
	Recovery	-0.0001	0.0041***	-0.0085***	-0.0127***
	Exit	-0.0206***	-0.0245***	-0.0123***	0.0122***
Labour	Remain as zombie	0.0044*	0.0064**	0.0016	-0.0048
	Recovery	0.0122***	0.0074***	0.0230***	0.0155***
	Exit	-0.0167***	-0.0139***	-0.0247***	-0.0107**
Leverage	Remain as zombie	-0.0186***	-0.0344***	0.0123**	0.0468***
	Recovery	-0.0361***	-0.0220***	-0.0670***	-0.0449***
	Exit	0.0547***	0.0565***	0.0546***	-0.0018
Low turbulence industries					
A. Expected probabilities: $\Pr(Y_{i,t+1} = j)$					
	Remain as zombie	0.7270***	0.74961***	0.67110***	-0.0785***
	Recovery	0.1747***	0.15663***	0.21004***	0.0534***
	Exit	0.0982***	0.09375***	0.11885***	0.0250***
B. Average marginal effects (AME): $\partial p_j / \partial \kappa_k$					
TFP	Remain as zombie	-0.0133*	-0.0089	-0.0206	-0.0116
	Recovery	0.0627***	0.0595***	0.0706***	0.0110
	Exit	-0.0493***	-0.0505***	-0.0499***	0.0006
Capital	Remain as zombie	0.0028	0.0031	0.0023	-0.0008
	Recovery	0.0018	0.0019	0.0016	-0.0003
	Exit	-0.0047	-0.0051	-0.0039	0.0011
Labour	Remain as zombie	0.0105	0.0075	0.0176	0.0100
	Recovery	0.0036	0.0047	0.0018	-0.0029
	Exit	-0.0141***	-0.0123**	-0.0194**	-0.0071
Leverage	Remain as zombie	0.0047	-0.0083	0.0301**	0.03850*
	Recovery	-0.0493***	-0.0403***	-0.0681***	-0.0277**
	Exit	0.0446***	0.0487***	0.0379***	-0.0107

Notes: Estimates from multinomial logistic model for high and low turbulence industries. High turbulence industries account for the most turbulent 20% of 3-digit industries, while low turbulence industries account for the least turbulent 20% of 3-digit industries. TFP, Capital, Labour and Leverage are in logs. IR is a dummy for the post-reforms zombies. The pairwise comparison between marginal effects express the interaction effect, that is, the difference in effects between the "zombies after the reforms" and the "zombies before the reforms". Unreported are estimates of control variables including log of EBITDA, log of age, log of zombie duration, business cycle measure, and industry and location dummies. *** p<0.01, ** p<0.05, * p<0.1.

Table C.5 Expected probabilities, Average marginal effects and differences between pre- and post-reforms periods, Multinomial logistic regression - Robustness Check Using Schivardi et al. (2017) Definition of Zombies

Covariate	Transition	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Pairwise comparison (Post minus Pre-reforms) (4)
A. Expected probabilities: $\Pr(Y_{i,t+1} = j)$					
	Remain as zombie	0.6714***	0.6851***	0.6237***	–0.0614***
	Recovery	0.1879***	0.1730***	0.2359***	0.0629***
	Exit	0.1407***	0.1419***	0.1403***	–0.0015
B. Average marginal effects (AME): $\partial p_j / \partial \kappa_k$					
TFP	Remain as zombie	0.0142***	0.0297***	–0.0285***	-0.0582***
	Recovery	0.0524***	0.0388***	0.0921***	0.0533***
	Exit	–0.0666***	–0.0685***	–0.0636***	0.0049**
Leverage	Remain as zombie	–0.0038	–0.0129***	0.0200***	0.0330***
	Recovery	–0.0809***	–0.0745***	–0.0991***	–0.0245***
	Exit	0.0847***	0.0874***	0.0790***	–0.0084***

Notes: TFP and Leverage are in logs. IR is a dummy for the post-reforms period. The pairwise comparison between marginal effects express the interaction effect, that is, the difference in effects between the "zombies after the reforms" and the "zombies before the reforms". Unreported are estimates of control variables including log of EBITDA, log of age, log of zombie duration, business cycle measure, industry- and location-dummies. *** p<0.01, ** p<0.05, * p<0.1.

Table C.6 Expected probabilities at average size (Capital and Labour), Multinomial logistic regression - Robustness Check Using Schivardi et al. (2017) Definition of Zombies

Variable	Transition	Size	2005-2016 (1)	IR = 0 (2)	IR = 1 (3)	Difference in expected probabilities (4) = [(3) – (2)]	Pairwise comparison (Large vs SME) (5)
Capital	Remain as zombie	SME	0.6692***	0.6839***	0.6228***	–0.0612***	–0.0373***
		Large	0.6958***	0.7203***	0.6218***	–0.0985***	
	Recovery	SME	0.1901***	0.1751***	0.2364***	0.0612***	0.0176***
		Large	0.1677***	0.1484***	0.2273***	0.0788***	
	Exit	SME	0.1407***	0.1409***	0.1408***	–0.0001	0.0197***
		Large	0.1365***	0.1313***	0.1509***	0.0197***	
Labour	Remain as zombie	SME	0.6740***	0.6870***	0.6263***	–0.0606***	0.0231***
		Large	0.6870***	0.6940***	0.6565***	–0.0375***	
	Recovery	SME	0.1874***	0.1726***	0.2356***	0.0630***	–0.0046
		Large	0.2210***	0.2075***	0.2660***	0.0585***	
	Exit	SME	0.1386***	0.1404***	0.1381***	–0.0024	–0.0186***
		Large	0.0920***	0.0985***	0.0775***	–0.0210***	

Notes: IR is a dummy for the post-reforms period. Columns (1), (2) and (3) reports the estimated probabilities for the "average" firm in each representative value (sample average of ln(capital) and ln(labour)), 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 express the interaction effect in each representative size-value. Unreported are estimates of TFP, leverage and the control variables including log of EBITDA, log of age, log of zombie duration, business cycle measure, and industry and location dummies. Standard errors (not reported) for statistical significance tests are obtained using the delta-method. *** p<0.01, ** p<0.05, * p<0.1.

Table C.7 Employment growth, Fixed-effects panel regression - Robustness check using zombie-share variable

Variable	(1)	(2)	(3)	(4)
TFP	0.1214***	0.1234***	0.0962***	0.0997***
	(0.0026)	(0.0026)	(0.0017)	(0.0017)
Employment-weighted zombie share	–0.3002***	–0.2275***		
	(0.0196)	(0.0253)		
TFP × Employment-weighted zombie	–0.3294***	–0.4302***		
	(0.0328)	(0.0363)		
Employment-weighted zombie share		–0.1232***		
		(0.0287)		
TFP × Employment-weighted zombie		0.1522***		
		(0.0223)		
Capital-weighted zombie share			–0.0881***	–0.0178
			(0.0138)	(0.0142)
TFP × Capital-weighted zombie share			0.0249	–0.0343**
			(0.0152)	(0.0162)
Capital-weighted zombie share × IR				–0.3850***
				(0.0136)
TFP × Capital-weighted zombie share				0.0065
				(0.0169)
Observations	1,742,104	1,742,104	1,742,104	1,742,104
R-squared	0.1972	0.1972	0.1969	0.1977
Number of firms	245,885	245,885	245,885	245,885

Notes: Employment-growth is measure as difference in logs. Employment (capital) weighted zombie share measures the proportion of total employment (capital) residing in zombies by industry (2-digit CAE). IR is a dummy for the post-reforms period. Unreported are estimates of control variables (log of initial employment, business cycle measure, interaction between TFP and business cycle measure, and year, industry and location dummies). The variables were winsorized at the 1st and 99th percentiles. Firm-cluster standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table C.8 Capital growth, Fixed-effects panel regression - Robustness check using zombie-share variable

Variable	(1)	(2)	(3)	(4)
TFP	0.0702***	0.0711***	0.0809***	0.0865***
	(0.0017)	(0.0017)	(0.0026)	(0.0026)
Capital-weighted zombie share	–0.1456***	–0.1068***		
	(0.0138)	(0.0141)		
TFP × Capital-weighted zombie share	–0.1157***	–0.1814***		
	(0.0143)	(0.0155)		
Capital-weighted zombie share × IR		–0.1958***		
		(0.0133)		
TFP × Capital-weighted zombie share × IR		0.1112***		
		(0.0165)		
Employment-weighted zombie share			–0.6379***	–0.4242***
			(0.0213)	(0.0253)
TFP × Employment-weighted zombie share			–0.3102***	–0.5768***
			(0.0327)	(0.0354)
Employment-weighted zombie share × IR				–0.3674***
				(0.0293)
TFP × Employment-weighted zombie share × IR				0.3954***
				(0.0223)
Observations	1,742,104	1,742,104	1,742,104	1,742,104
R-squared	0.1679	0.1682	0.1687	0.1691
Number of firms	245,885	245,885	245,885	245,885

Notes: Employment-growth is measure as difference in logs. Employment (capital) weighted zombie share measures the proportion of total employment (capital) residing in zombies by industry (2-digit CAE). IR is a dummy for the post-reforms period. Unreported are estimates of control variables (log of initial employment, log of initial capital, business cycle measure, interaction between TFP and business cycle measure, and year, industry and location dummies). The variables were winsorized at the 1st and 99th percentiles. Firm-cluster standard errors are given in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D

Table D.1 Summary of long-term creative destruction trends in Portugal during 1986-2018

Chapter	Indicators	During the late 20th century			During the new century		
		Economy-wide	KIA sector	Non-KIA sector	Economy-wide	KIA sector	Non-KIA sector
5th	Entry rate	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
	Employment share of entrants	Constant	Increasing	Constant	Decreasing	Decreasing	Decreasing
	Survival likelihood of entrants	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
	Employment share of young firms	Constant	Increasing	Constant	Decreasing	Decreasing	Decreasing
	The net job creation rate	Positive and constant	Increasing	Positive and constant	Decreasing until 2010, Increasing thereafter	Decreasing until 2010, Increasing thereafter	Decreasing until 2010, Increasing thereafter
	Job reallocation rate	Increasing	Increasing	Increasing	Decreasing	Decreasing	Decreasing
	Dispersion of the employment-weighted growth rate distribution	Increasing	Increasing	Constant	Decreasing	Decreasing	Decreasing
	Positive skewness of the employment-weighted growth rate distribution	Increasing	Increasing	Constant	Decreasing until 2010, Increasing thereafter	Decreasing until 2010, Increasing thereafter	Decreasing until 2010, Increasing thereafter
	The growth rate of high-growth firms	Increasing	Increasing	Constant	Decreasing until 2010, Increasing thereafter	Decreasing	Decreasing until 2010, Increasing thereafter
	The growth rate of high-growth young firms	Increasing	Increasing	Increasing	Increasing	Decreasing	Increasing
6th	Instability of market shares	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
	Sales concentration	Constant	Decreasing	Constant	Increasing	Increasing	Increasing
	Leadership persistence rate	Increasing	Decreasing	Increasing	Increasing	Increasing	Increasing
	The technological gap between leaders and followers	Decreasing	Increasing	Decreasing	Increasing	Decreasing	Increasing
	The innovation gap between leaders and followers	Decreasing (still positive)	Constant (still positive)	Decreasing (still positive)	Decreasing (zero in 2018)	Decreasing (zero in 2018)	Decreasing (zero in 2018)
7th	Incidence of zombie firms	N/A	N/A	N/A	Increasing until 2012, Decreasing thereafter	Increasing until 2012, Decreasing thereafter	Increasing until 2012, Decreasing thereafter

Note: The table summarises the main findings regarding the long-term trends of the Portuguese industrial dynamics. Methodological issues are in the corresponding chapter