Industrial dynamics throughout the ICT innovation cycle: The rise and decline of business dynamism in Portugal during 1986-2018

Ernesto Nieto-Carrillo
University of Coimbra, Centre for Business and Economics Research, CeBER and Faculty of Economics

Carlos Carreira
University of Coimbra Centre for Business and Economics, CeBER and Faculty of Economics

Paulino Teixeira
University of Coimbra, Centre for Business and Economics, CeBER and Faculty of Economics

CeBER Working Papers
No. 3 / 2023

CeBER is funded by the Foundation for Science and Technology, I.P.

Industrial dynamics throughout the ICT innovation cycle: The rise and decline of business dynamism in Portugal during 1986-2018

Ernesto Nieto-Carrillo[1]*, Carlos Carreira, and Paulino Teixeira*

University of Coimbra and CeBER

Abstract

Increasing evidence shows that business dynamism has weakened in most developed economies. However, except for the US literature, most previous research has only portrayed the new century's changes in firm dynamics. Instead, we focus on a longer period, 1986-2018, assembling an extensive longitudinal database with a time-consistent industry classification covering the population of Portuguese firms in the manufacturing and service sectors. The Bai-Perron estimate for unknown break dates in time series indicates two structural changes in industrial dynamics, one in its ascending wave (1993) and another in the declining phase (2003). Accordingly, our (HP) estimated trends show that, after an initial period of intense creative destruction, firm dynamics have become less turbulent since 2003, with lower entry, declined job reallocation, and decreased growth rates. Furthermore, survival and counterfactual firm-level regressions suggest that an otherwise-equal post-2003 start-up faced a significantly higher exit hazard than its pre-1993 counterpart (i.e., without any structural change). As a result, new and young companies have seen their share in aggregate employment and net job creation decline, notwithstanding the increasingly higher performance of young, high-growth firms. Lower labour and firm turnover suggest a weakened contribution of reallocation to productivity growth. On the other hand, decreased entry and the higher exit hazard have likely undermined the disruptive potential of transformative entrepreneurship.

KEYWORDS: Firm dynamics; Entry; High-growth firms; Resource reallocation; Survival.

[1] Corresponding author. E-mail: enietoc@fe.uc.pt

1 Introduction

Schumpeter (1942) claimed that creative destruction is the fundamental impulse that keeps the capitalist machine in motion through incessant innovations that make old ideas and technologies obsolete. Hence, vigorous economic growth generally entails higher firms and labour turnover rates generated by the required creative destruction process (Aghion & Akcigit, 2019; Dosi & Nelson, 2010). Its long-term dynamic properties, in turn, critically depend on a permanent entry and growth 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 (Decker et al., 2014; Geroski, 1995).

Nevertheless, increasing evidence shows that reallocation and entrepreneurship rates have declined in most developed countries during the new century and before the pandemic crisis (Decker et al., 2016; Calvino et al., 2020). Moreover, this phenomenon has occurred concurrently with greater within-industry productivity dispersion (Andrews et al., 2015) and increased industrial concentration (Bajgar et al., 2019; Autor et al., 2017). All this happening along with a well-known persistent productivity slowdown.

We contribute to this literature by analysing the industrial dynamics patterns throughout the ICT innovation cycle, particularly by exploring entry and exit rates, job reallocation, post-entry growth and survival dynamics in Portugal from 1986 to 2018.[2] Given the lack of proper extended, longitudinal, micro-level and multisector data, exploring the long-run trends of business dynamism is not an easy endeavour. To address this task, we have compiled a novel and rich longitudinal dataset covering the universe of firms operating in the manufacturing and service sectors.

The beginning of our exploration coincides with the emergence of the technological paradigm linked to the ICT revolution. It is also concurrent with Portugal's adhesion to the European Union and the consequent currency change and enlargement of the trade borders. Hence, the observed business dynamics likely 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). Furthermore, as Nelson (2008) and Perez (2010) emphasise, technological paradigms tend to yield diminishing returns once their potential has been exhausted. As a result, business dynamism is likely to slow down when such creative burnout takes place. We accordingly compare knowledge-intensive activities (KIA) versus non-knowledge-intensive ones intending to capture the different productive trajectories resulting from the emergence of the ICT technological paradigm.

[2] After a robust economic expansion during the 1990s, output and productivity growth rates in Portugal have remained stagnant since 2000, while the labour share has fallen by about 10 percentage points between 2000 and 2018.[2] This phenomenon has been exacerbated by the counter-productive destruction that occurred during the 2008-2013 Portuguese crisis.

Most previous research has been based on new-century evidence. The sole exception, to our knowledge, are the works by Decker et al. (2014, 2016, 2018) and Bijnens and Konings (2020), who analysed long-term industrial trends in the US (1979-2013) and Belgium (1985-2014), respectively. Our estimated (HP) trends show that the secular decline in business dynamism is far from a country-specific phenomenon. Nevertheless, our results only partly confirm those obtained in these previous studies.

Firstly, Portugal's economy-wide growth rate dispersion and reallocation showed an upward dynamism during the late 20th century, in contrast to a downward pattern observed in the US and Belgium since the early 1990s. *Secondly*, Decker et al. (2016, 2018) and Bijnens and Konings (2020) reported a declining share of new and young firms in employment since the 1990s. Instead, we found that infant firms' employment share and net job creation were robust and persistent through the 1990s, decreasing only since 2000. *Thirdly*, the skewness of the growth rate distribution followed the growing dispersion pattern during the 1990s in our case, while Decker et al. (2016) reported an upward skewness and a downward dispersion in the US, and Bijnens and Konings (2020) pointed out that both indicators displayed declining trends in Belgium since the early 1990s.

Fourthly, Decker et al. (2016) argue that a decreasing presence of young firms in job creation and aggregate employment is related to a lower propensity of young firms to become high-growth units. Yet, as in Bijnens and Konings (2020), the lower young firms prevalence in Portugal occurred even though infant companies were growing more rapidly. *Finally*, although economy-wide trends are quite replicated across common forms of sectorial disaggregation, we observe markedly differentiated patterns between the KIA and Non-KIA sectors, particularly during the 1990s. On the whole, our results indicate intense creative destruction during the late 20th century—mainly driven by expanding knowledge-intensive activities (KIA)—, followed by collapsing business dynamism in the post-2000 era.

We extend previous studies by estimating structural changes in industrial dynamics and the variation in exit risk of young firms due to those structural changes. Accordingly, the Bai-Perron estimate for unknown break dates in (pure) time series indicates structural breaks occurring in 1993 and 2003 (Bai & Perron, 1998; Ditzen et al., 2021). Afterwards, the null hypothesis of no breaks was rejected in all the economy-wide and sectorial industrial dynamics indicators. Interestingly, the 1993 and 2003 break dates coincide with the ascending and declining phases of business dynamism observed in our trend estimations. Finally, survival and counterfactual firm-level regressions suggest that an otherwise-equal post-2003 start-up faced a significantly higher exit hazard than its pre-1993 counterpart (i.e., without any structural change).

The relatively higher turnover rate of firms and labour in knowledge-intensive sectors during the 1990s highlights the ICT technological paradigm's role in bringing back economic growth. However, business dynamism has critically declined in the KIA and non-KIA industries in the post-2003 era, likely impairing the contribution of resource reallocation to productivity growth. Furthermore, despite a significant improvement in the performance of a typical high-growth young firm, the incidence of newly-born enterprises declined during the new century. Our results highlight that decreased entry and the higher exit hazard have likely undermined the disruptive potential of transformative entrepreneurship.

The remainder of the paper is organised as follows: in section 2, we review the previous literature on the long-run behaviour of industrial dynamics and productivity growth; section 3 describes the dataset and the methodology. Then, the estimation results are shown and discussed in section 4. Finally, section 5 presents the main conclusions and some topics for future research.

2 Literature review

2.1 Industrial dynamics and productivity growth in the long-term perspective

Market selection and productivity-enhancing reallocation are critical determinants of long-run growth (Aghion and Akcigit, 2019; Dosi and Nelson, 2010). As Aghion and Akcigit (2019) point out, more vigorous economic expansion generally entails a higher rate of firm and labour turnover generated by the required process of creative destruction. In evolutionary models of industrial dynamics, although entry and survival are more productively challenging in the industry's mature phase, turbulence (as far as market shares are concerned) is expected to persist (Winter et al., 2000; 2003). The economy-wide reallocation/turbulence would also be continuously fuelled by creating new markets and production methods.

In these approaches, long-term dynamic properties critically depend on a permanent inflow of technologically heterogeneous firms, expected to nurture technological change, allow prices to get right, and prevent the entrenchment of monopolies (Robinson. 1969; Schumpeter, 1942). In Acemoglu et al. (2018), there is an adverse selection throughout the firm life cycle, where companies are expected to be more productive and innovative when young. This conjecture has been confirmed by Alon et al. (2018), who found a downward-sloping relationship between firm age and productivity.

The evolutionary perspective warns, however, that innovation and entrepreneurship opportunities are ultimately constrained by the prevailing technological paradigm (Dosi & Nelson, 2010; Perez, 2010).[3] Technological paradigms would 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). Thus, when the knowledge base has been virtually exhausted, inventiveness dries out, the return on innovation diminishes, business dynamism slows, and markets most likely concentrate sales on companies with the leading technology (Nelson, 2008).[4] On the other hand, industrial life cycle literature suggests that, beyond sectoral specificities, each phase of market evolution

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

[4] 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.

appears to follow specific common patterns (Geroski, 1995; Klepper, 1997). First, 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 decline due to, for example, the preponderance of process innovation, which tends to favour large incumbents. Finally, in the mature stage, 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.

Here, it is critical to emphasise that declined business dynamism does not necessarily imply poor economic performance as long as market selection depends on efficiency and innovation differentials (Decker et al., 2018). Nevertheless, well-documented evidence suggests that non-competitive mechanisms also operate in markets, which precisely appear to become more critical as industries reach maturity and when concentration rates are higher.

In particular, 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 at a mature industry stage when economies of scale play a predominant role (Geroski, 1995). Network effects and ill-designed patent regimes would also penalise entry and weaken the development of survivors (Stiglitz and Greenwald, 2015; Grullon et al., 2019). Moreover, the empirical record indicates that incumbent firms are aware of entrepreneurial heterogeneity. Therefore, deterrence mechanisms are expected to operate rather 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 in turn by the high incentive that young innovative entrepreneurs would have to sell their company at a very attractive price (Stiglitz and Greenwald, 2015).

Contrary to Schumpeter, Robinson (1969) claimed that the competitive mechanism tends to weaken as markets evolve due to scale effects and increasing financial constraints. As a result, 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.

In this regard, the evidence shows that financially constrained, though productive, firms face a higher failure risk and grow slower (Musso and Schiavo, 2008; Carreira and Teixeira, 2016; Carreira et al., 2021), with these restrictions being more severe for young and small enterprises (Aghion et al., 2007). Bottazzi et al. (2014) and Lee (2014) also found that financial constraints prevent fast-growing young companies from seizing attractive growth opportunities. Schneider and Veugelers (2010) further indicate that access to finance is the most important factor hindering the knowledge activities of innovative firms, especially if they are young. Accordingly, in the long run, increasing risk, concentration, and the rising cost of technology are likely to impair finance availability and thus hinder the entry and growth of the 'liveliest would-be innovators' (Stiglitz and Greenwald, 2015; Robinson, 1962).

2.2 The long-run evidence on business dynamism and resource reallocation

Growing evidence shows that business dynamism and resource reallocation weakened in most developed economies over the past few decades and before the pandemic crisis (Decker et al., 2016; Calvino et al., 2020). This phenomenon has been concomitant with a widespread increase in market concentration (De Loecker et al., 2020; Bajgar et al., 2019; Affeldt et al., 2021) and within-industry productivity dispersion (Andrews et al., 2015; Decker et al., 2018).

Decker et al. (2016) and Alon et al. (2018) reported, for the US economy, that the entrepreneurship rate has declined steadily since the 1980s, accompanied by a lower share of young firms in aggregate employment. Decker et al. (2016) further observed that the employment growth rate distribution has 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 average industrial age is now higher (Alon et al., 2018).

According to Alon et al. (2018), the start-up deficit and the industry's ageing would have led to an annual drop of 0.1 p.p. in the US aggregate productivity growth rate during 1980-2014 (i.e., a cumulative effect of 3.1 p.p.). Concurrently, the economy-wide job reallocation rate has fallen by about 10 p.p. between 1979 and 2011 (Hathaway and Litan, 2014). Thus, declined entrepreneurship, slower post-entry growth, and decreased reallocation imply a weakened selection effect on technological efficiency growth, as evidenced 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.

Calvino et al. (2020) observed similar decreasing trends in business dynamism, resource reallocation, and young firms' activity in the rest of the OECD countries. According to the authors, although there is a connexion between the heterogeneity of institutional settings and the nature of the business dynamism slowdown, these secular trends transcend specific national contexts. However, given that their analysis only covers the period 2000-2015, their findings are not directly comparable to those of Decker et al. (2016, 2018) and Alon et al. (2018). Most importantly, these medium-term studies preclude determining whether there was a structural breaking point in the industrial dynamics patterns.

To our knowledge, the only equivalent inquiry outside the US is that conducted by Bijnens and Konings (2020), who analysed the Belgian firm 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. Bijnens and Konings (2020) accordingly indicate that 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.

Weakening business dynamism, more concentrated markets with old and entrenched leaders, and slowing technological change suggest that creative destruction is running out of steam. However, economists are far from reaching a consensus on its causes. On the one hand, Decker et al. (2018)—albeit not ruling out increased entry barriers due to greater concentration—suggest that the rising adjustment costs would be rooted in stronger intervention, especially in the labour market.[5] In turn, Autor et al. (2017) propose that enhanced information flow led by ICT usage enabled consumers to become more sensitive to price and quality differentials, thus enabling '*superstar firms to take all*.' Similarly, Aghion et al. (2022) argue that the increased preponderance of intangible assets gave leading companies a process efficiency advantage challenging to imitate, so the technological gap became very persistent. Thus, a more significant efficiency advantage has encouraged market leaders to expand into broader product lines, increasing productivity but discouraging new innovators over time (due to lower expected profit margins).

In contrast, Covarrubias et al. (2020) argue that the US economic behaviour has evolved from 'good' (during the 1990s) to 'bad' concentration (from the new century on), where mergers and acquisitions and lobbying spending by dominant firms have triggered an increase in entry costs. Furthermore, Akcigit and Ates (2019) 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, for instance—negatively affects current and potential competition, favouring concentrated sectors' prevalence.

Economists from other theoretical strands have further suggested that a declining industrial dynamism and increasing market concentration are rooted in a 'corporate-biased regulation' (Lambert, 2019; Mazzucato et al., 2020; Stiglitz, 2019). Stiglitz (2019) claims that, in the absence of appropriate public intervention, monopoly, once achieved, is easy to maintain, and, from there, "rent-seeking" behaviour is likely to prevail. According to Stiglitz, large companies would have specialised in developing "innovations" to expand their monopoly 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). 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.

[5] However, we note that, according to the OECD index in employment protection, the US economy has one of the most flexible labour markets within developed countries, and increasingly so since the 80s. See the OECD Employment Outlook 2020: Worker Security and the COVID-19 Crisis | OECD Employment Outlook", available at: https://www.oecd-ilibrary.org/employment/oecd-employment-outlook-2020_1686c758-en

3 Data and Methodology

3.1 A long-standing novel dataset with time-consistent industry classification

Our primary data is *QP–Quadros de Pessoal*, a longitudinal employer-employee dataset covering the population of firms operating in all sectors except domestic services. This data has been collected annually by the Ministry of Employment since 1985 and provides enterprise- and establishment-level information on the business structure and employment.[6] To complement the industrial information, we also use *FUE-Ficheiro de Unidades Estatísticas* and *SCIE-Sistema de Contas Integradas das Empresas*, two sources collected by the National Statistical Office (INE) during 1996-2004 and 2004-2018, respectively. These two datasets share the same firm identification number of QP and report, among other variables, the economic activity at the highest level of disaggregation of the population of corporations.

Over the sample period, three industrial classification methodologies have been in place: CAE Rev. 1 (1985-1994), CAE Rev. 2 (1995-2006), and CAE Rev. 3 (2004 onwards). These changes introduce limitations for conducting any long-term analysis that requires industrial affiliation. Therefore, we implemented a homogenisation process to build time-consistent industry codes. The objective was to classify all firms under Rev. 2, at least at 2-digits of disaggregation.[7]

Following Fort and Klimek (2018) and Autor et al. (2017), we applied the following three-step procedure: i) we 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, we 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;[8] and iii) we performed a modal mapping only in the remaining cases (5.32% of total observations), so each industry Rev.1 and Rev.3 was assigned the 2-digit Rev.2 code more likely to be mapped to in the probabilistic mapping, determined by the mode.

Afterwards, preliminary filtering of the raw data was required. In particular, companies not belonging to the productive sector (e.g., foundations) and unreasonable observations (e.g., negative employment) were eliminated.[9] We then select our sample keeping only the

[6] The participation of firms with registered employees is mandatory, providing high coverage and reliability. Moreover, each company and worker have a unique identification number, allowing tracking them longitudinally and generating firm-level variables from the establishment and worker data.

[7] Given that QP had industry codes at a maximum of only 3-digits in 1985-2009 and 4-digits from 2010 onwards, we 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 firms 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.

[8] To illustrate, in the case of multiple destinations of companies operating before and from 2007, we assigned the 2-digit code they had before that year, provided they remained in the same industry after that.

[9] To estimate firm growth, job creation, and job destruction rates, we generate observations (with employment equal to zero) for the years a company temporarily did not report to QP—which was interpreted as a temporary

industrial sector and part of the service sector to obtain the following subset: manufacturing, construction, wholesale and retail trade, accommodation and food services, and real estate, renting and business support services sectors, and travel agencies and transport-related services, and recreational, cultural and sports activities subsectors. Our final sample comprises an unbalanced panel of 896,827 companies, totalling 7,534,119 year-firm observations containing new, continuing, and exiting firms.

3.2 Business dynamics statistics

Our study starts with the computation of entry and exit rates. Prior experience working with the QP suggests that a company may not temporarily report to the survey for reasons other than the cessation of activity (Mata & Portugal, 2004). Hence, the exit of a given firm is identified in the year following the last time the firm reports positive employment. Temporary closings are not then considered exits. Similarly, entry is flagged the first time the company reports positive employment, which implies that reopenings are excluded.[10] QP also has information at the plant level, but plant identifiers depend directly on firm identifiers. Hence, we cannot distinguish between an involuntary closure and the change resulting from a merger or acquisition, as the plant identifier changes accordingly. However, previous evidence indicates that these events are very unusual in the Portuguese economy (Mata & Portugal, 2004), so our 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, we 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 (Haltiwanger et al., 2009). To compute employment growth rates, we follow the approach of Davis et al. (1996) (DHS rate from now on), which are calculated as follows:

$$g_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{X_{i,t}}, (1)$$

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 $X_{i,t} = \frac{E_{i,t}+E_{i,t-1}}{2}$.[11] As Haltiwanger et al. (2013) point out, using the average employment as a denominator aims to neutralise the

closure—and for the year following the last time it reported positive employment—interpreted as a definitive exit (see more details in the next section).

[10] 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."

[11] Following Haltiwanger et al. (2009), job flows are computed as follows: $JCR_{s,t} = \sum_{\substack{i\in s \\ g_{i,t}\geq 0}} \left(\frac{X_{i,t}}{X_{s,t}}\right) g_{i,t}$; $JDR_{s,t} = \sum_{\substack{i\in s \\ g_{i,t}<0}} \left(\frac{X_{i,t}}{X_{s,t}}\right) |g_{i,t}|$; $JRR_{s,t} = JCR_{s,t} + JDR_{s,t}$, 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.

"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 DHS rate's distribution is bounded between 2 (for entries and reopenings, in our case) and -2 (for exits and temporary closings).[12]

Next, we examine the employment-weighted growth rate distribution. We observe young firms' performance compared with mature firms by inspecting the dispersion and skewness statistics.[13] The age is constructed based on the entry year, and young firms are those with less than five years.[14] Then, we calculate young firms' annual share in net job creation (i.e., creation minus destruction) and aggregate employment. The typical performance of a high-growth firm (HGF) is observed 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, the study of the behaviour of a typical young HGF is critical to observe how the quality of entrepreneurship and mobility barriers have evolved.

Our long sample period allows us to isolate the effect of the business cycle. Thus, we use the Hodrick Prescott filter (HP) to separate the time series into trend and cyclic components. Given the annual nature of the information, the smoothing parameter is set to 100. Finally, we 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, we use the methodology developed by EUROSTAT. Table A1 in the Appendix Section shows the list of industries classified as knowledge-intensive (at two digits).

3.3 Structural break estimation and survival analysis

A key element of our empirical strategy is estimating potential structural breaking points "*B*" in the Portuguese industrial dynamics patterns resulting from the economic shocks throughout the ICT innovation cycle. Since we do not want to impose potential breakpoints arbitrarily, we employ Bai & Perron's (1998) framework to estimate unknown break dates in univariate time series. Thus, let us assume that an aggregate industrial dynamics measure varies around a long-run mean δ_0, so that:

$$y_t = \delta_0 + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2), \tag{5}$$

where y_t is the dependent variable denoting an industrial dynamics variable in the year t, and ε_t is the noise component with $E[\varepsilon_t] = 0$ and $E[\varepsilon_t^2] = \sigma^2$. As measures of industrial

[12] 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.

[13] 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.

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

dynamics, we use, in separate runs, two of the most critical creative destruction variables, namely, the job reallocation rate (JRR) and the dispersion of the employment-weighted growth rate distribution (i.e., the 90-10 differential), calculated as shown in the previous section. The aim is to identify if there were structural breaks in the long-run (unconditional) mean δ_0. Thus, under the alternative hypothesis H_1, y_t is subject to structural breaks on unknown dates T_b, that is:

$$y_t = \delta_0 + \sum_{b=1}^{B} \delta_b d_b(t > T_b) + \varepsilon_t, \tag{6}$$

where $d_b(.)$ is an indicator of the event "*the structural break occurred in T_b*". To estimate the break date, the approach divides the sample at each possible breaking point. Then, it estimates the parameters using ordinary least squares, computing and storing the sum of squared errors. The least-squares estimate of the break date is the date that minimises the full-sample sum of the squared errors (Dating & Hansen, 2001; Ditzen et al., 2021). Since we allow for serial correlation and heteroscedasticity in the errors, we specify a HAC covariance estimation. In particular, we tested the hypothesis of "no breaks" *versus* "two breaks" (trying to capture the influence of the paradigm's rise and fall).[15] Yet, we pay special attention to the existence of a breaking point in the business dynamism's declining stage. Once breaking points have been detected, if any, we perform the test on all the other measures of business dynamism, but now with *known break dates*. We conduct this procedure at aggregated and disaggregated levels (i.e., KIA and Non-KIA sectors).

Subsequently, our inquiry seeks to identify whether there was a change in the risk of exit for a typical start-up after the identified structural breaks. To this end, we employ survival analysis, observing the behaviour of new firm cohorts born from 1986 onwards.[16] The failure event corresponds to exiting the market in t+1. The age, based on the entry year, reports the survival time and whether failure or censoring occurs in each period. To focus on infant firms' survival, each entrant leaves the sample when reaching maturity (i.e., from five years old onwards, in our setting).[17] Once the survival data is declared, we specify a hazard model as follows:

$$h\left(t \middle| x_{i,t}\right) = h_0(t) * \exp\{d_b(\cdot)'\boldsymbol{\theta_b} + \boldsymbol{X}'\boldsymbol{\Omega}\}, \tag{7}$$

The hazard function $h(t)$ is the instantaneous failure rate, that is, the (limiting) probability that the failure event (i.e., exiting the market) occurs in t+1. We do not make any assumption about the *baseline hazard* $h_0(t)$, therefore, our estimation method is the semi-parametric Cox Proportional Hazard model (Cleves et al., 2010). Moreover, since our information is annual, we cannot observe the exact moment of the failure event (i.e., we have "tied failures" every period). Thus, we apply Breslow's "handling ties" method to solve this issue.

[15] However, we perform robustness tests allowing a lower number of breaks based on the minimum period of time between two breaks, which was set at 15% of the total observations.

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

[17] Notice that "leaving the sample after reaching maturity" and "exiting the market" are entirely different events. Therefore, there is no failure event when a young company reaches maturity and is still active.

Matrix $\boldsymbol{X}$ contains our control variables, namely the log of initial size, the DHS firm growth rate, a dummy for knowledge-intensive activities, a business cycle measure (calculated as the cyclical component of net job creation by region), and location dummies. To control for differences in human capital across entrants, we use worker-level information to compute the share of skilled labour in the firm's total number of employees. Skilled workers are those with high-school levels and above.

The variable $d_b(.)$ is the indicator variable for each interval after each structural break, with our base category $d_b = 0$ corresponding to all young firms *before* the first identified break date. Hence, we are interested in comparing the exit hazard of a typical start-up after each breaking point with that of the entrants' base category, given by the corresponding coefficients in $\boldsymbol{\theta_b}$. Since the dependent variable is the hazard rate, a negative (positive) coefficient implies that the corresponding variable reduces (increases) the instantaneous probability of exiting the market, which increases (decreases) the chance of survival. We expect a positive sign in the coefficient associated with the survival regime during the new century, meaning that survival for infant firms has become more difficult. As a robustness check, we also perform a binary logistic regression on the probability of exiting the market in $t + 1$. In that case, we include the age of the entrant as an additional control variable. All continuous variables were winsorised at the 1st and 99th percentiles.

3.4 Counterfactual model

Estimating a structural change in the entrants' survival regime through hazard or binary probability models may be seriously affected by unobserved firm heterogeneity, especially if such heterogeneity conditions the probability of entering the market before or after a breakpoint. For instance, if the structural break discouraged the entry of more (idiosyncratically) innovative firms, lower survival may result from an entry excessively populated by low-productivity enterprises. Alternatively, we could assume each company has an intrinsic "frailty" (shared across time) and estimate a hazard regression. However, shared frailty models are essentially random effects specifications that cannot control for endogeneity issues. These concerns are particularly relevant in our case, where idiosyncratic firm characteristics are likely correlated with the likelihood of entry before or after the (potential) structural break. Furthermore, the baseline exit likelihood (i.e., $h_0(t)$ in the specification (7) or $(\exp \beta_0)/(1 + \exp \beta_0)$ in the logistic model) is expected to be the same throughout the sample period, which may also be a strong assumption in our setting.

An ideal experiment would, therefore, randomly assign entrepreneurs before and after break dates. However, since such an experiment is not feasible, we apply a standard counterfactual outcomes model (Rubin, 1974) to estimate the difference in hazard risk between two otherwise-equal newly-born firms when only one is affected by a structural break. Since we allow for multiple break dates in the survival regime, we apply, in particular, a potential outcome framework with multivalued treatment effects (Wooldridge, 2010). Hence, let us denote the binary outcome variable as $\mathrm{Y_{i,t+1}}$, which takes the value of one if an infant firm exits the market in $t + 1$ and zero otherwise. Furthermore, let us designate $\mathrm{Y_{0,i,t+1}}$ as the potential outcome of an infant firm that does not face any structural change in the survival regime (i.e., the control group). Therefore, since $d_b(.)$ is an indicator of the event "*the structural break occurred in* T_b", we have $\mathrm{Y_{b,i,t+1}}$ if $d_b = 1$ and $\mathrm{Y_{0,i,t+1}}$ if $d_b = 0$, so that:

$$Y_{i,t+1} = (1 - d_b)Y_{0,i,t+1} + d_b\left(Y_{b,i,t+1}\right), \tag{8}$$

where $b \in \{1, \dots, B\}$ contains each of the survival regimes before and after potential breaking points. Moreover, assuming that the exit likelihood of entrant firms (i.e., $P\left[\mathrm{Y_{i,t+1}} = 1\right]$) is a function of the covariates contained in Matrix $\boldsymbol{X}$ (including firm age), we have that:

$$E\left[Y_{i,t+1}\right] = P\left[Y_{i,t+1} = 1|\boldsymbol{X_{i,t}}\right] = F\left(\boldsymbol{X_{i,t}}'\boldsymbol{B}\right), \tag{9}$$

Finally, assuming conditional mean independence and common support, the average treatment effect (ATE) and the average treatment effect on the treated (ATET) are given by:

$$ATE = E\left[Y_{b,i,t+1}|\boldsymbol{X_{i,t}}\ \right] - E\left[Y_{0,i,t+1}|\boldsymbol{X_{i,t}}\ \right], \tag{10}$$

$$ATET = E\left[Y_{\tilde{b},i,t+1}|\boldsymbol{X_{i,t}}, b = \tilde{b}\ \right] - E\left[Y_{0,i,t+1}|\boldsymbol{X_{i,t}}, b = \tilde{b}\right], \tag{11}$$

where $b = \tilde{b}$ confines the expectation to include only those infant firms that actually face the structural change in the survival regime.

To estimate the ATE and ATET, we employ the "regression adjustment" model. This approach allows obtaining the treatment effects without assuming any specific functional form for the treatment assignment process. The regression adjustment estimator performs separate regressions for each treatment level and uses averages of expected outcomes for the whole sample to estimate potential outcome means (Cameron & Trivedi, 2005). In particular, we employ logistic regressions to predict the exit risk of entrants. Yet, we also use a probit binary probability model to predict the outcome variable as a robustness check.

4 Results

4.1 Firm and labour turnover rates

We begin our analysis by exploring the Hodrick-Prescott (HP) business dynamism trends, paying particular attention to the knowledge-intensive activities (KIA) sector. Panel A of Figure 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.[18] However, looking at job creation trends, we notice that the contribution of start-ups to job creation declines after 2000. The share of new firms actually 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

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

6% in 2000 to about 3% in 2018. Finally, note that the net entry rate and the net job creation by entrants turned negative between 2004 and 2006, remaining so until 2018.

[Insert Figure 1 here]

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 mature industries (where entry and survival are more stringent) outweigh nascent ones in the long run, a decrease in the entry rate and an increase in the exit rate is relatively predictable. However, entrants' negative net firm formation and net job creation 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, bearing in mind the industrial life cycle theory, 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 "Knowledge Intensive Activities (KIA)" sector and the rest of the industries (panel A of Figure 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 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. However, the net firm formation has become visibly negative only in the Non-KIA sector (since 2006).

[Insert Figure 2 here]

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 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. Namely, a constant trend in job creation during the 1990s and a decreasing one 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.

In Figure 3, we observe 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 4 p.p. higher in the KIA sector. However, both creation and destruction have fallen sharply since 2000. The decline in the KIA sector is sudden: job creation decreased 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.

[Insert Figure 3 here]

The collapse of job creation and destruction led to a drastic drop in the reallocation rate during the new century. Figure 4 shows that job reallocation first showed an increasing pattern between 1986 and 2000, from 28% to 35%. Job reallocation was also more intense in the KIA sector, whose rate increased from 21% in 1986 to 42% in 2000. Nevertheless, there has been a secular decline in reallocation in the new century. 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 the Appendix section, we confirm that this sharp decline in reallocation has been ubiquitous in the new century era.[19]

[Insert Figure 4 here]

4.2 Growth rate 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 two decades. However, it remains to be understood whether a deterioration in post-entry growth accompanied the decline in the entrepreneurship rate.

Previous evidence suggests that the post-entry stage of infant firms is characterised by an intense "up-or-out" dynamic (Coad et al., 2014; Decker et al., 2014). In other words, they exhibit high mortality along with strong growth of survivors. Conditioned on survival, young firms show a much higher net growth rate than their mature counterparts. However, Decker et al. (2014) stress that young companies' average net growth rate masks much heterogeneity. The growth rate distribution of young exhibits a greater dispersion and positive skewness than their mature counterparts. Therefore, young firms' high average net growth rate would be skewed by those in the distribution's right tail, which are supposed to offset losses resulting from the early death of weaker entrants. For this reason, the largest contribution of entrepreneurship to creative destruction is expected to come from young, high-growth firms.

[19] In the Appendix section, we also look at entry, exit, job creation, job destruction, and job reallocation rates in particular sectors, and the secular trends seem to follow a common pattern.

Against this backdrop, we start by analysing the incidence of young firms in aggregate employment and net job creation. In this fashion, we evaluate the hypothesis of a constant aggregate contribution from infant enterprises. Even with a smaller entry rate, a steady contribution of young firms is still possible whenever newly-born firms are increasingly more innovative and productive and, as a result, grow more than their previous counterparts (especially those fast-growing ones).

Our results show, however, a declining incidence of infant firms in the Portuguese economy during the current century. In panel A of Figure 5, in line with the entrant firms' patterns, we note that the economy-wide employment share of young companies remains relatively constant until the late 90s. Nevertheless, 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. As for the knowledge intensity level of industries (panel B), notice that the proportion of young firms in the KIA sector's employment has a rather rising slope until 2000. Yet, this share has fallen in the new century, from 30% in 2003 to 14% in 2018. In the Non-KIA sector, young firms maintained a relatively constant share until the 1990s. But it also started to decline after 2000. The weakened position of young companies in aggregate employment thus indicates that an overall ageing of industries is likely to have taken place.[20]

[Insert Figure 5 here]

Meanwhile, as we observe in Figure 6, the contribution of young firms (including newly born enterprises) to net job creation has also been reduced during the new century. Young firms certainly generate the largest contribution to net job creation. In contrast, mature firms are net job destroyers, with net job creation rates below zero. However, while young companies still contribute the most during the new century, their economy-wide net job creation rate has roughly fallen from 8% to 4% (panel A). Interestingly, mature firms' share has shown an upward trend since 2010, somehow compensating for the lower contribution from infant firms. Furthermore, we observe that the fall in the net job creation by young firms has been more significant in the KIA sector, in such a way that the contribution of these companies has been equalised in both sectors (panel B). Considering such declining young firms' contribution, it is therefore 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.

[Insert Figure 6 here]

Figure 7 shows the annual evolution of the 90-10 differential 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). First, 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 are not driven by the observed entry and exit rate

[20] In the Appendix section, we confirm these findings in the analysis by sectorial economic specialisation.

changes.[21] Second, in line with reallocation patterns, the analysis reveals an economy-wide dispersion that increases until the late 90s and declines thereafter. 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 new century, reaching a 90-10 differential similar to that of 1990.

[Insert Figure 7 here]

Figure 8 shows the dispersion of the employment-weighted growth rate distribution differentiated by age groups. Confirming earlier studies, we first observe that the growth rate distribution of young firms exhibits a greater dispersion (i.e., with a higher 90-10 differential). Afterwards, our findings show that the growth rate distribution of young and mature firms follows opposite dispersion patterns. The dispersion trend of mature firms is similar to that observed throughout the economy, showing a distribution contraction during the new century. Instead, the dispersion of young companies increases over the entire 1990-2018 period. Specifically, the 90-10 differential of young firms' growth rate distribution increased from 0.74 p.p. to 0.95 p.p. between 1990 and 2018 (i.e., 21 p.p.). Therefore, although not strong enough to sustain economy-wide trends, job reallocation within young firms appears to have been increasingly intense from 1990 to 2018.

[Insert Figure 8 here]

To further characterise the growth rate distribution, we analyse the evolution of the 90-50 and 50-10 differentials for all and continuing firms in Figure 9. First, we note that, unlike what happened with the dispersion, the presence of new and exiting companies does influence the skewness pattern. Specifically, 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, our estimates indicate that positive skewness across the economy increased until the late 1990s, declining after that and throughout the new century's first decade. However, the distribution is again more right-skewed after 2010.[22] 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 is what explains most of the positive-skewness increase. Thus, the skewness follows the dispersion pattern between 1986 and 2010.[23] 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, laggard firms appear to have improved their performance over the last decade.

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

[22] Notice that the gap between the 90-50 and 50-10 differentials of continuing firms is about 5 p.p. in 2000, 1 p.p. in 2010, and 10 p.p. in 2018.

[23] 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).

[Insert Figure 9 here]

Figure 9 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 in 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, would also be explained by the KIA sector's dynamics (in this sector, the trend 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)* positive skewness decreased between 2000 and 2010 in the KIA and Non-KIA sectors; *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 at the sectoral level or across the economy, especially over the last decade. So *first*, Figure 10 also confirms that the growth rate distribution of young firms shows greater positive skewness than mature firms (i.e., the ratio between the 90-50 and 50-10 differentials is greater). *Second*, the positive skewness widens in both categories during the 1990s, although this enlargement is significantly higher in young companies. This result supports that infant firms played a key role in the strong job creation observed in the Portuguese economy at the end of the 20th century. *Third*, distributions of young and mature firms exhibited less positive skewness during 2000-2010, caused by both a narrowing of the 90-50 differential and a widening of the 50-10 differential. *Fourth*, positive skewness increases from 2010 on in both cases. However, this increase is explained in mature firms by narrowing the 50-10 differential. This fact implies that laggard mature companies of the last decade appear to have grown *less slowly* than their preceding counterparts. Instead, the widening of the 90-50 differential accounts for the larger positive skewness exhibited by the distribution of young companies since 2010. Accordingly, young firms in the distribution's right tail appear to have continued performing better 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.

[Insert Figure 10 here]

Figure 11 finally presents the evolution of high-growth firms (HGF) (i.e., the 90th percentile of the growth rate distribution). On the one hand, following skewness patterns, we observe that a typical HGF exhibited (even) higher rates during the 1990s, followed by a decline since 2000 and a slight recovery after 2010. On the other, confirming our previous expectations, our estimates indicate that young firms in the distribution's 90th percentile have shown increasingly higher growth rates. Using secular trend estimates, we observe that the 90th percentile young firms' growth rate distribution increased from 47% in 1990 to 54% in 2000, finally reaching 66% in 2018 (i.e., 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 increase in the late 1990s and 2010s, has remained relatively constant. Clearly, mature HGFs grow at a slower rate than young HGFs.[24]

[Insert Figure 11 here]

In short, the evidence suggests that, while economy-wide reallocation and growth rate dynamics collapsed during the new century with reduced dispersion (and growth rates clustered around a zero median) and lower right tail distribution performance, young firms showed increasingly higher growth rates during 1990-2018 (especially those in the 90th percentile of the distribution). Nonetheless, this improved performance of high-growth young firms seems not to have compensated for the lower entry, as new and young firms reduced their share of net job creation and aggregate employment. These patterns are common across all industries.

4.3 A structural change in job reallocation and the survival regime

Two main facts emerged from the results of the previous sections. On the one hand, the Portuguese business dynamics of the last four decades exhibited two markedly differentiated patterns. A phase of intense creative destruction, characterised by a high contribution from new and young firms, strong job reallocation, and highly dispersed and right-skewed growth rate distribution, followed by a sharp decline in all indicators during the new century. On the other hand, although high-growth young firms exhibited increasing performance, the share of new and young firms in aggregate employment and net job creation declined, meaning they were not able to offset an overall lower entry rate. Hence, we proceed now to estimate whether decreased industrial dynamics result from a structural break and whether this systemic change conditioned the survival regime of infant firms.

Table 1 shows the results of the Bai & Perron (1998) estimator and test for *unknown* breakpoints. The alternative hypothesis H_1 proposes that job reallocation and growth rate dispersion faced two structural breaks (thus changing their long-term mean). In contrast, the null hypothesis H_0 indicates no breaks throughout the sample period. Our findings strongly reject the null hypothesis since the W(tau) statistic is highly significant in both cases. At the same time, it is critical to highlight that the identified break years in both indicators were 1993 and 2003, which, as Figure 12 shows, precisely coincide with the rise and decline of reallocation and growth rate dispersion trends in Portugal.[25]

[Insert Table 1 and Figure 12 here]

Once identified the break dates, we wondered if the other business dynamics variables suffered the same structural changes. Accordingly, Table 2 shows the results of the Bai & Perron (1998) test for *known* breakpoints, whose alternative hypothesis H_1 proposes structural breaks in the long-term mean of each industrial dynamics variable ocurring in 1993

[24] In the Appendix section, we show HGFs trends for all enterprises (i.e., including entering and exiting firms), and the results generally hold.

[25] As a robustness check, we test the hyphotesis of $H_0 = 1$ breaking point versus $H_1 = 2$ breaks. Our results reject the null hypothesis in favor of two structural changes in industrial dynamics.

and 2003. The results again reject the null hypothesis of no breaks, with a highly significant W(tau) statistic in all measures. Thus, on the whole, our findings suggest a structural rise in industrial dynamics starting in 1993 and a structural decline starting in 2003.

[Insert Table 2 here]

As the next step, we repeat the estimation and test procedure for each sector broken down by knowledge intensity level. Table 3 shows that the null hypothesis of no break is rejected in favour of two breakpoints in both variables. In the Non-KIA sector, the break dates are 1993 and 2003 for job reallocation and growth rate dispersion. In the KIA sector, for its part, the break years in job reallocation are 1993 and 2004, while the break dates are 1993 and 2003 in the growth rate dispersion.

[Insert Table 3 here]

Table 4, finally, presents the results of the structural break test for known breakpoints for KIA and Non-KIA industries. Given that our preferred creative destruction measure is the job reallocation (creation plus destruction) rate, the break years to evaluate are 1993 and 2004 for the KIA sector and 1993 and 2003 for the Non-KIA one. Once again, the null hypothesis of no breaks is strongly rejected in the KIA and Non-KIA sectors for all indicators. Our findings confirm structural changes in industrial dynamics patterns, with a systemic decline during the new century, even in knowledge-intensive industries.

[Insert Table 4 here]

Given these structural breaks in business dynamics, an open question is whether there was also a change in the survival regime of entrants, especially considering that infant firms' employment and net job creation shares fell despite the better performance of young HGFs. As mentioned, the post-entry phase of young firms is characterised by "up-or-out" dynamics, with infant firms exiting during the first five years of life (Decker et al., 2014). This high early mortality rate appears to result from an overpopulated entry of "subsistence" enterprises, which 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 (Geroski, 1995).

Accordingly, the industry lifecycle theory suggests that mobility barriers, such as scale economies, technological intensity, and advertising intensity, are more relevant when industries reach maturity, and the market tends to favour the survival and expansion of large and older "deep-pocket" incumbents (Geroski, 1995; Klepper, 1997). Likewise, the evolutionary approach argues that long-term innovation cycles tend to yield diminishing returns when technological opportunities have been widely exploited (Dosi & Nelson, 2010; Perez, 2010). Until a new paradigm emerges, creative destruction is likely to slow down with weakened entry of products, technologies, and thus markets. Therefore, if ageing is a common feature of industries, it is not difficult to conjecture a greater incidence of mobility barriers during the declining phase of creative destruction.

Table 5 presents the results of the semi-parametric Cox regression and the binary logistic model on the entrants' likelihood of exiting the market. We confirm that the larger the firm (in terms of employment), the lower the exit hazard. The estimations also show that a higher share of skilled labour is associated with a lower hazard rate, whereas the higher the employment growth rate, the lower the exit probability. More importantly, our findings suggest that the entrant survival probability has decreased more and more after each break date (i.e., 1993 and 2003), as shown by the positive and highly significant coefficients associated with our structural changes indicator. Since our base category in the 1986-1992 survival regime, our Cox-regression estimates show that, while newly-born firms in 1993-2002 faced a 1.11 times greater hazard $[= \exp(0.1021)]$ than in the period prior to the first structural change (i.e. over 1986-1992), young firms in the post-2003 break faced a 1.35 times higher exit risk $[= \exp(0.3031)]$ than their counterparts not facing any structural change. Moreover, as shown in Figure 13, there is a clear upward shift in the infants' hazard function after each break date, conditional on Cox regression estimates. The binary logit probability regression confirms these findings. We interpret these findings as preliminary evidence in favour of a higher exit risk of newly-born firms, particularly during the declining stage of industrial dynamics.

[Insert Table 5 and Figure 13 here]

Exit risk estimates, however, might be biased if self-selection conditioned the entry of new firms before or after structural breaks. Therefore, we see in Table 6 the results of our counterfactual model in which we estimate the difference in the exit probability of two equally productive entrants (proxied by size, growth rate, human capital, and age and controlled for unobserved heterogeneity) facing the same environment (proxied by the business cycle and location indicators), but one enters before a structural break, and the other enters after that. Thus, we observe that the treatment effects are highly significant, showing that *treated* infant firms (i.e., entering after the break date) exhibited a greater exit risk than their counterfactual newly born enterprises (i.e., entering before any break). Moreover, this higher exit hazard is especially relevant for young firms affected by the second structural change (i.e., in 2003). Specifically, our results indicate that the 2003-2018 survival regime increased the likelihood of exiting the market, on the treated entrants, from 10.62% (i.e., potential outcome mean) to 15.23%, an increase of 4.6 percentage points (see specification (1)).

Consequently, our 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. During the period of intense creative destruction, higher exit risk seems to have been compensated by a better performance of fast-growing infant firms, as new and young firms' aggregate contributions remained constant. However, the incidence of young firms in aggregate employment and net job creation has declined during the declining phase of industrial dynamics despite the better performance of high-growth young firms. The structural break in creative destruction is thus reflected in lower turbulence and more stringent entry and survival.

[Insert Table 6 here]

5 Conclusions and final remarks

Economists of different theoretical strands have increasingly studied business dynamism. The main focus of interest lies in the turnover rates of firms and labour as critical indicators of intense creative destruction. Vigorous entrepreneurship, without structural obstacles, in particular, ensures that competition forces boost growth. As such, one can only understand capitalism by analysing its long-term path. Many, generally opposing forces operate simultaneously in markets. Some push for growth and innovation, while others try to circumvent selection forces to facilitate an accumulation sans investment. The prevailing regime thus determines the long-run growth and distribution patterns. The institutional setting (including deregulation) plays a critical role in shaping the trajectory of an economy, which may encourage *creative destruction* or, inversely, *destructive creation* (Mazzucato, 2013).

Our results suggest two structural changes in Portuguese industrial dynamics, one in the ascending industrial dynamics wave (1993) and another in its declining phase (2003). Indeed, Bai & Perron's (1998) tests for structural breaks strongly reject the null hypothesis of no breaks in all business dynamism indicators, including job reallocation and new and young firms' contribution.

Accordingly, our (HP) estimated trends show that Portugal's late 20th century was characterised by intense creative destruction, driven critically by the rise of knowledge-intensive activities. Until 2003, the entry and contribution of new market players were vigorous despite the higher exit risk of entrants during the 90s. Concurrently, an increasing job reallocation occurred, with a positive trend favouring job creation. This dynamism led to increased dispersion of the growth rate distribution, driven mainly by a more significant 90-50 percentile differential and an increasing share of high-growth firms. A continuous aggregate efficiency improvement is, therefore, likely to have occurred. The increase in all business dynamism indicators was also more pronounced in the knowledge-intensive activities (KIA) sector, revealing the dominant role of industries that *directly* incorporated the new driving technological paradigm in aggregate performance.

Nevertheless, industrial dynamics became less turbulent after the 2003 structural break. New enterprises' entry and their total employment share have fallen sharply. As a result, both (net) firm and job creation rates by entrants have become negative, the KIA sector inclusive. Moreover, the reallocation rate and the dispersion of the growth rate distribution declined sharply, which has likely undermined aggregate efficiency growth as well. 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 HGFs. Since knowledge-intensive activities are more innovative and generate high value-added, from which other industries benefit, their slowdown is likely to have hampered long-term technological progress.

Although young firms have had higher growth rates, especially those in the 90th percentile, they have not offset the lower business entry and survival. Nor is it observed that the higher performance of young companies impacted mature firms, whose distribution has rather exhibited a concentration at median growth rates. Moreover, counterfactual estimations indicate that an otherwise-equal infant firm faced a 4.6 percentage points higher exit likelihood after the 2003 breaking point than its pre-1993 break counterpart (i.e., our control group without any structural change). As a result, new and young companies have seen their share in aggregate employment and net job creation decline.

Therefore, our estimates confirm that the secular decline in business dynamism is not a country-specific phenomenon. In addition, the evidence suggests that mobility barriers have undermined business dynamism, particularly for new and young firms, limiting their ability to 'shake out' the established order. While the "catch-up" process of mature (laggard) firms enabled their contribution to net job creation to be more significant over the past decade, the start-up deficit and industry ageing have likely caused job creation and productivity growth to be trapped into inertia and rent-seeking behaviour. Further research is thus required to determine the impact of decreased entrepreneurship and reallocation on growth and income distribution.

Is creative destruction sustainable in the long term, as suggested by Schumpeter? The technologically stagnant, more concentrated, and less dynamic industries characterising most advanced economies during the new century seem to indicate the opposite. The great technological shock linked to the ICT revolution has 'set and kept the capitalist engine in motion' for almost two decades. Nevertheless, economic dynamism has been undermined in the long run. Thus, neither turbulence nor newly born firms' contribution has remained constant. Notwithstanding the better performance of young enterprises, this seems to be the case in the Portuguese economy. Certainly, the battle among *old corporate giants* can still fuel competitive forces, but, as Robinson (1962) argued, they cannot be relied upon to maintain the continued pressure that constant job creation requires.

6 References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., & Kerr, W. (2018). Innovation, Reallocation and Growth. *The American Economic Review*, *108*(11), 3450–3491.

Affeldt, P. L., Duso, T., Gugler, K., & Piechucka, J. (2021). Market concentration in Europe: Evidence from antitrust markets. *DIW Discussion Papers*, *No. 1930*, 1–41.

Aghion, P., & Akcigit, U. (2019). Innovation and Growth: The Schumpeterian Perspective. In L. Matyas, R. Blundell, E. Cantillon, B. Chizzolini, M. Ivaldi, W. Leininger, R. Marimon, & F. Steen (Eds.), *Economics without Borders: Economic Research for European Policy Challenges* (pp. 29–72). Cambridge University Press.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., & Li, H. (2022). *A Theory of Falling Growth and Rising Rents*.

Aghion, P., Fally, T., & Scarpetta, S. (2007). Credit Constraints as a Barrier to the Entry and Post-Entry Growth of Firms. *Economic Policy*, *22*(52), 731–779.

Akcigit, U., & Ates, S. T. (2019). Ten facts on declining business dynamism and lessons from endogenous growth theory. *NBER Working Paper Series*, *25755*, 1–44.

Alon, T., Berger, D., Dent, R., & Pugsley, B. (2018). Older and Slower: The Start-up Deficit's Lasting Effects on Aggregate Productivity Growth. *Journal of Monetary Economics*, *93*(2018), 68–85.

Andrews, D., Criscuolo, C., & Gal, P. N. (2015). Frontier Firms, Technology Diffusion and Public Policy. *OECD: The Future of Productivity: Main Background Papers.*

Autor, D., Dorn, D., Katz, L., Patterson, C., & Van Reenen, J. (2017). The Fall of the Labor Share and the Rise of Superstar Firms. *NBER Working Paper Series*, *23396*.

Bai, J., & Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, *66*(1), 47.

Bajgar, M., Berlingieri, G., Criscuolo, C., & Calligaris, S. (2019). Industry Concentration in Europe and North America. *OECD Productivity Working Papers*, *No. 18*, 1–53.

Bellone, F., Musso, P., Nesta, L., & Quéré, M. (2008). Market selection along the firm life cycle. *Industrial and Corporate Change*, *17*(4), 753–777.

Bijnens, G., & Konings, J. (2020). Declining business dynamism in Belgium. *Small Business Economics*, *54*, 1201–1239.

Bottazzi, G., Secchi, A., & Tamagni, F. (2014). Financial constraints and firm dynamics. *Small Business Economics*, *42*(1), 99–116.

Calvino, F., Criscuolo, C., & Verlhac, R. (2020). Declining business dynamism: Structural and policy determinants. *OECD Science, Technology and Innovation Policy Papers*, *No. 94*, 1–

74.

Cameron, C., & Trivedi, P. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Carreira, C., Teixeira, P., Nieto-Carrillo, E., & Eira, J. (2021). *Financial Constraints and Business Dynamics: Lessons from the 2008-2013 Recession*. Fundação Francisco Manuel dos Santos.

Cleves, M., Gould, W., Gutierrez, R., & Marchenko, Y. (2010). *An Introduction to Survival Analysis Using Stata* (3rd ed.). Stata Press.

Coad, A., Daunfeldt, S. O., Hölzl, W., Johansson, D., & Nightingale, P. (2014). High-growth firms: Introduction to the special section. *Industrial and Corporate Change*, *23*(1), 91–112.

Covarrubias, M., Gutiérrez, G., & Philippon, T. (2020). From good to bad concentration? Us industries over the past 30 years. *NBER Macroeconomics Annual*, *34*, 1–46.

Dating, C., & Hansen, B. E. (2001). The New Econometrics of Structural Change: Dating Breaks in US Labor Productivity. *Journal of Economic Perspectives*, *15*(4), 117–128.

Davis, S. J., Haltiwanger, J., & Schuh, S. (1996). Small business and job creation: Dissecting the myth and reassessing the facts. *Small Business Economics*, *8*, 297–315.

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, *135*(2), 561–644.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives*, *28*(3), 3–24.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2016). Where Has all the Skewness Gone? The Decline in High-growth (young) Firms in the US *European Economic Review*, *86*, 4–23.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2017). Declining dynamism, allocative efficiency, and the productivity slowdown. *The American Economic Review*, *107*(5), 322–326.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2018). Changing Business Dynamism and Productivity: Shocks vs Responsiveness. *NBER Working Paper Series*, *24236*, 1–65.

Ditzen, J., Karavias, Y., & Westerlund, J. (2021). *Testing and Estimating Structural Breaks in Time Series and Panel Data in Stata*. http://arxiv.org/abs/2110.14550

Dosi, G. (1982). Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change. *Research Policy*, *11*(3), 147–162.

Dosi, G., & Nelson, R. R. (2010). Technical Change and Industrial Dynamics as Evolutionary Processes. In B. Hall & N. Rosenberg (Eds.), *Handbook of Economics of Innovation* (pp. 52–127). North-Holland.

Fort, T. C., & Klimek, S. D. (2018). The Effects of Industry Classification Changes on US Employment Composition. *CES Working Paper Series*, *18*(28), 1–23.

Geroski, P. A. (1995). What do we know about entry? *International Journal of Industrial Organization*, *13*(4), 421–440.

Grullon, G., Larkin, Y., & Michaely, R. (2019). Are US Industries Becoming More Concentrated? *Review of Finance*, *23*(4), 697–743.

Haltiwanger, J., Jarmin, R., & Miranda, J. (2009). Business Dynamics Statistics: An Overview. *SSRN Electronic Journal*, *January*(1), 1–8.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, *95*(2), 347–361.

Hathaway, I., & Litan, R. E. (2014). Declining Business Dynamism in the United States: A Look at States and Metros. *Economic Studies at Brookings*, 1–7.

Klepper, S. (1997). Industry Life Cycles. *Industrial and Corporate Change*, *6*(1), 145–181.

Lambert, T. E. (2019). Monopoly capital and entrepreneurship: Whither small business? *Cambridge Journal of Economics*, *43*(6), 1577–1595.

Lee, N. (2014). What holds back high-growth firms? Evidence from UK SMEs. *Small Business Economics*, *43*(1), 183–195.

Mata, J., & Portugal, P. (2004). Patterns of entry, post-entry growth and survival. *Small Business Economics*, *22*(3–4), 283–298.

Mazzucato, M. (2013). Financing Innovation: Creative Destruction vs. Destructive Creation. *Industrial and Corporate Change*, *22*(4), 851–867.

Mazzucato, M., Ryan-Collins, J., & Gouzoulis, G. (2020). Theorising and mapping modern economic rents. *IIPP Working Paper Series*, *13*, 1–20.

Musso, P., & Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, *18*(2), 135–149.

Nelson, R. R. (2008). Why Do Firms Differ and How Does It Matter? A Revisation. *Seoul Journal of Economics*, *21*(4), 607–619.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics*, *34*(1), 185–202.

Robinson, J. (1962). *Essays in the Theory of Economic Growth*. Palgrave Macmillan.

Robinson, J. (1969). *The Accumulation of Capital* (3rd ed.). Palgrave Macmillan.

Rubin, D. B. (1974). Estimating causal effects of treatment in randomised and nonrandomised studies. *Journal of Educational Psychology*, *66*(5), 688–701.

Schneider, C., & Veugelers, R. (2010). On young highly innovative companies: Why they matter and how (not) to policy support them. *Industrial and Corporate Change*, *19*(4), 969–1007.

Schumpeter, J. A. (1939). *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process.* McGraw-Hill.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper and Brothers.

Stiglitz, J. E. (2019). *People, Power, and Profits: Progressive Capitalism for an Age of Discontent*. W. W. Norton & Company.

Stiglitz, J. E., & Greenwald, B. C. (2015). *Creating a Learning Society: A New Approach to Growth, Development, and Social Progress*. Columbia University Press.

Winter, S. G., Kaniovski, Y. M., & Dosi, G. (2000). Modeling Industrial Dynamics with innovative entrants. *Structural Change and Economic Dynamics*, *11*, 255–293.

Winter, S. G., Kaniovski, Y. M., & Dosi, G. (2003). A Baseline Model of Industry Evolution. *Journal of Evolutionary Economics*, *13*(4), 355–383.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

7 Figures and Tables

7.1 Figures

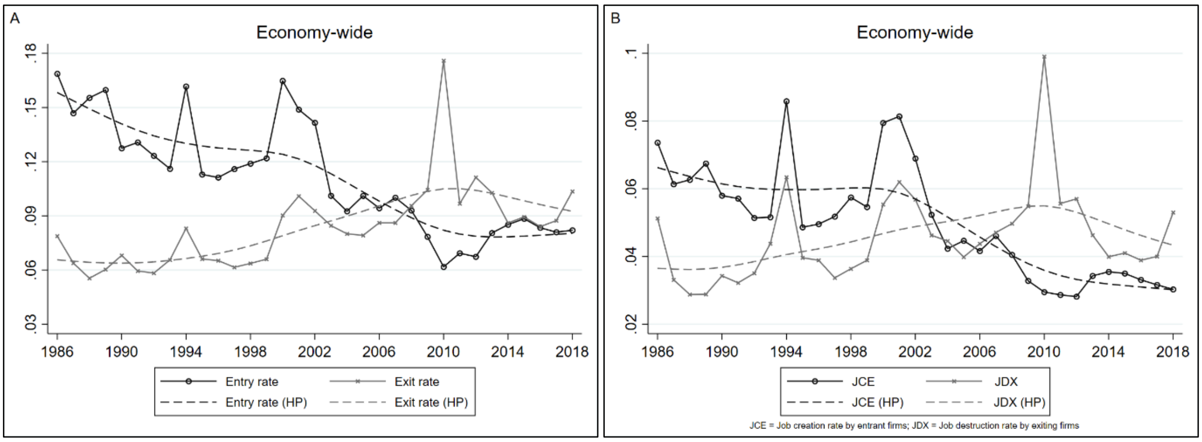

Figure 1. The share of entering and exiting firms, 1986-2018

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 (HP) filter with a smoothing parameter of 100. Y axis does not start at zero.

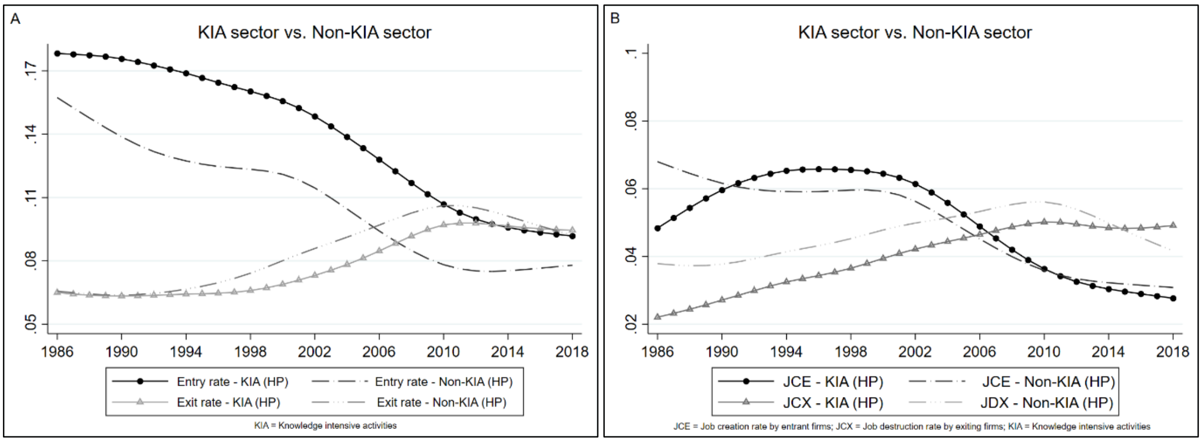

Figure 2 the share of entering and exiting firms by sector, 1986-2018

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 (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.

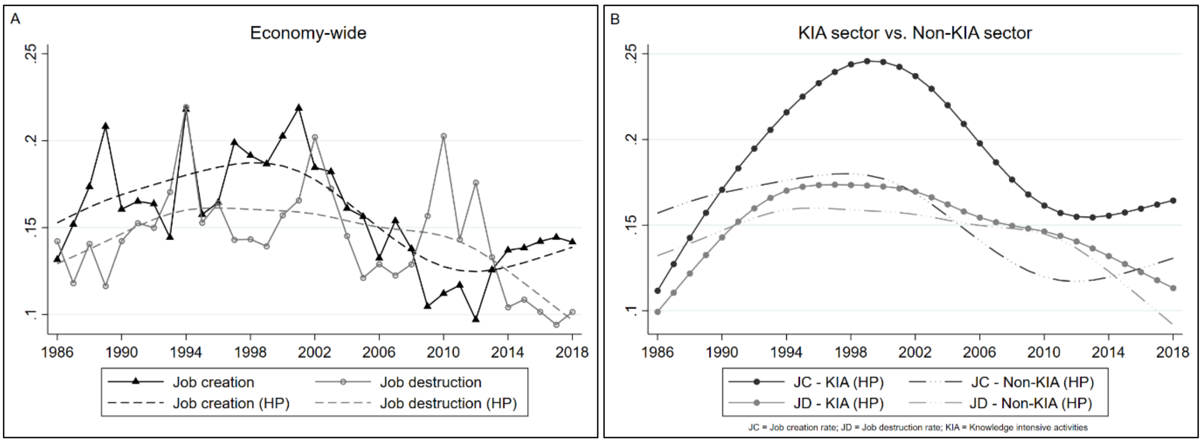

Figure 3. Job creation and destruction rates, 1986-2018

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 (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.

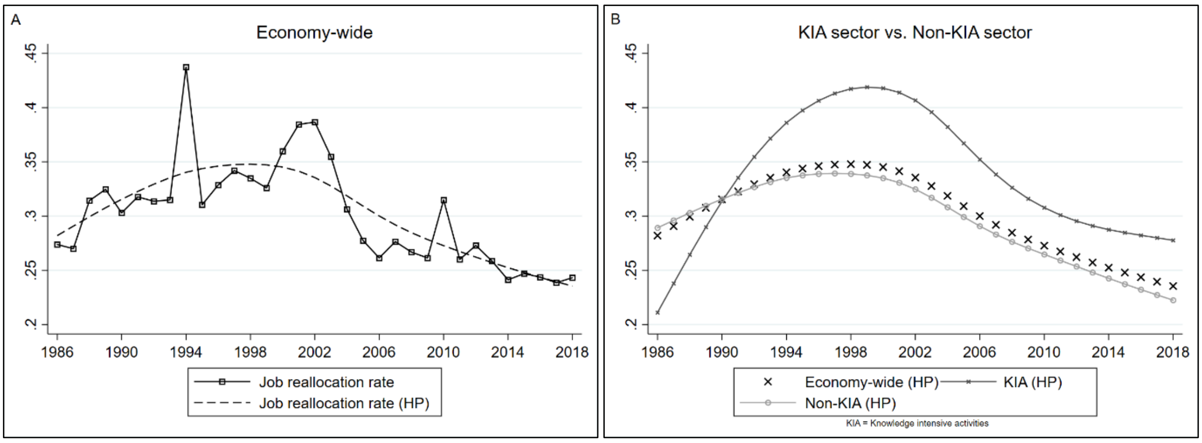

Figure 4. Job reallocation rate, 1986-2018

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 (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.

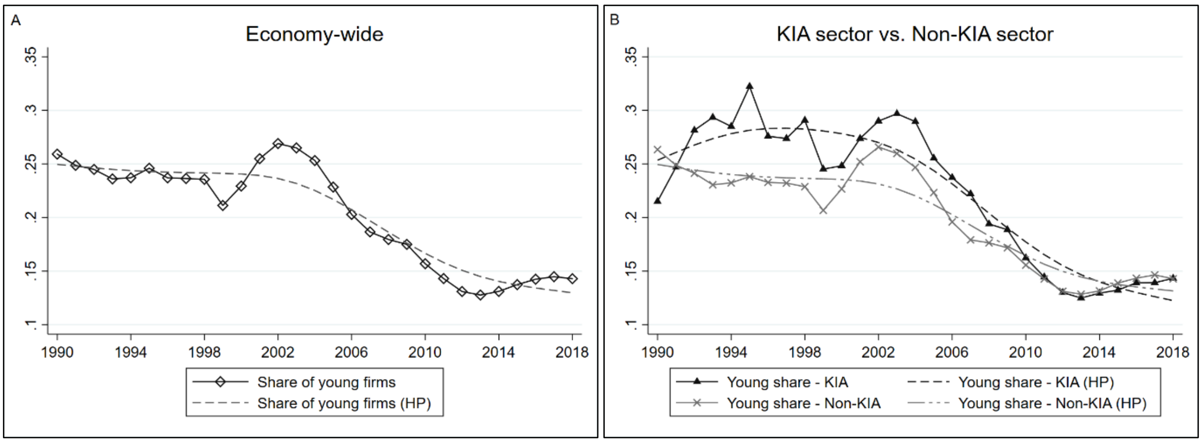

Figure 5. The employment-share of young firms, 1990-2018

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 (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.

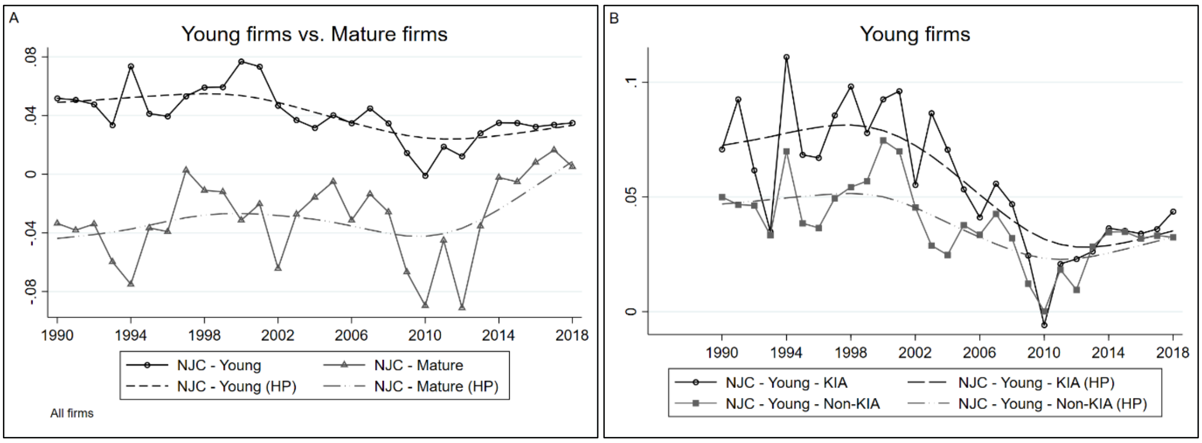

Figure 6. Net job creation rate by age, 1990-2018

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 (HP) filter with a smoothing parameter of 100.

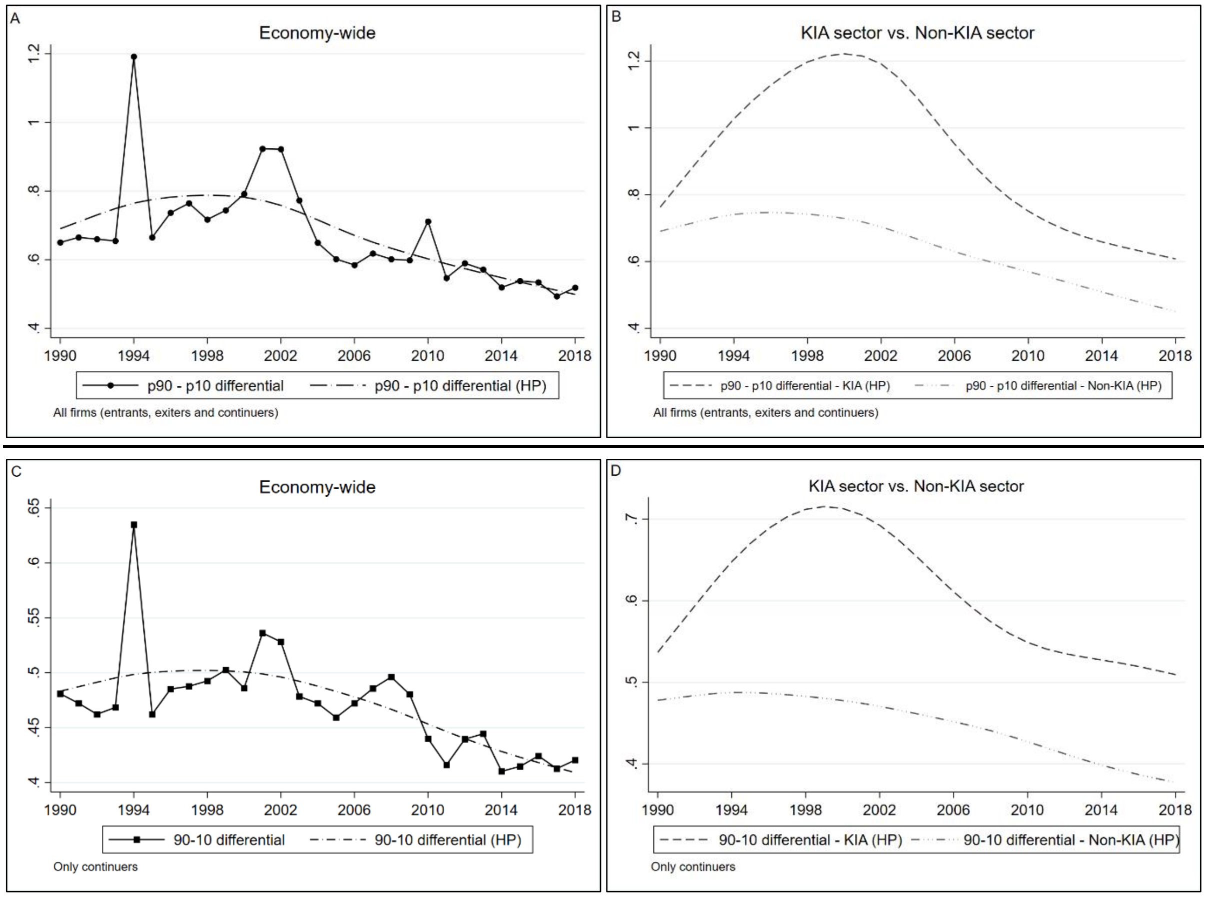

Figure 7. Dispersion of the employment-weighted growth rate distribution, 1990-2018

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 (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.

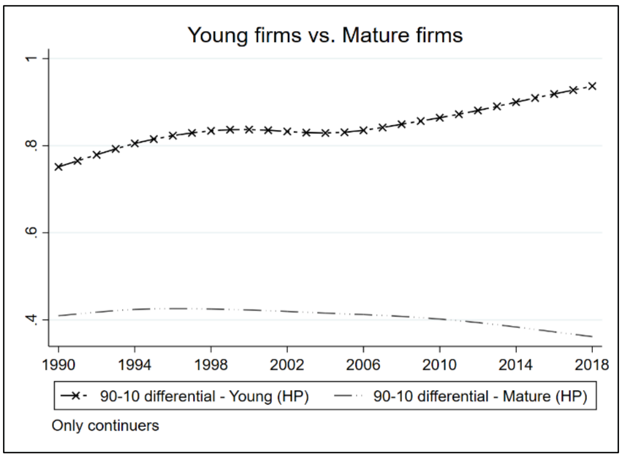

Figure 8. Dispersion of the employment-weighted growth rate distribution by age, 1990-2018

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 (HP) filter with a smoothing parameter of 100. Y axis does not start at zero.

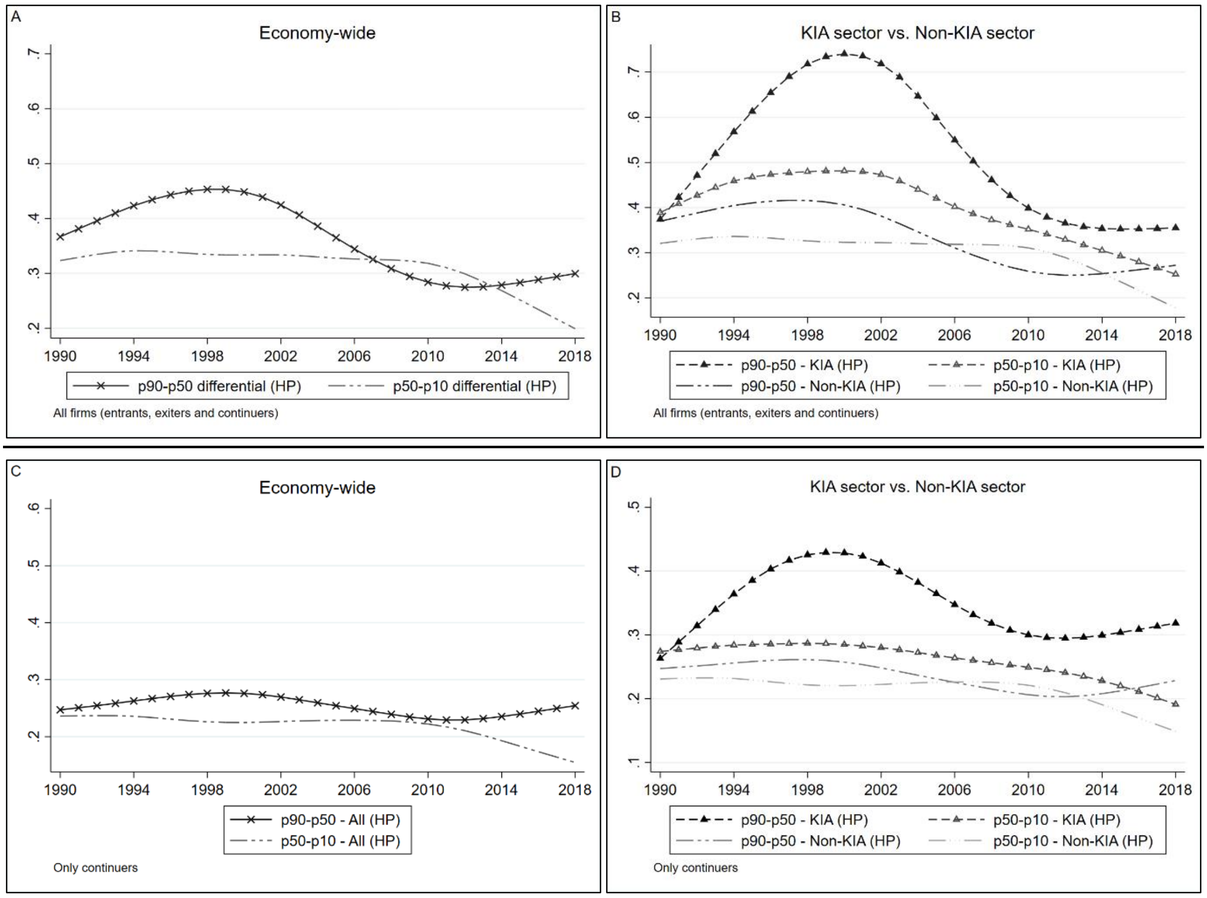

Figure 9. Skewness of the employment-weighted growth rate distribution, 1990-2018

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 (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.

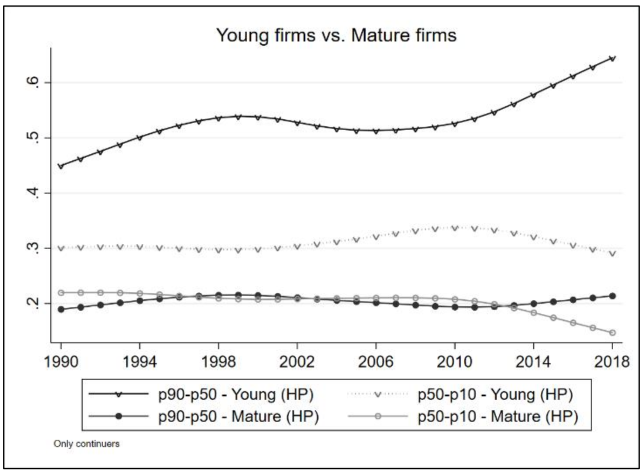

Figure 10. Skewness of the employment-weighted growth rate distribution by age, 1990-2018

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 (HP) filter with a smoothing parameter of 100. Y axis does not start at zero.

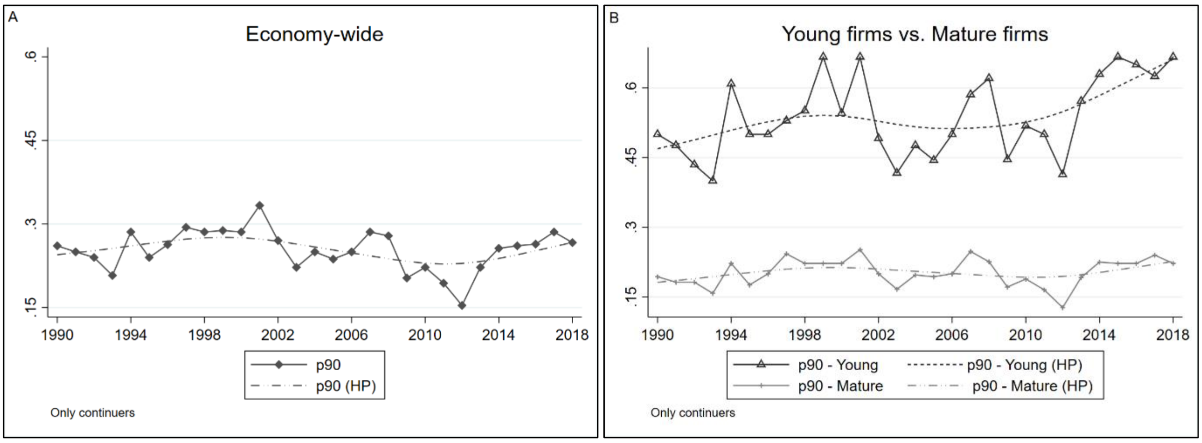

Figure 11. The evolution of high-growth firms, 1990-2018

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 (HP) filter with a smoothing parameter of 100. Y axis does not start at zero.

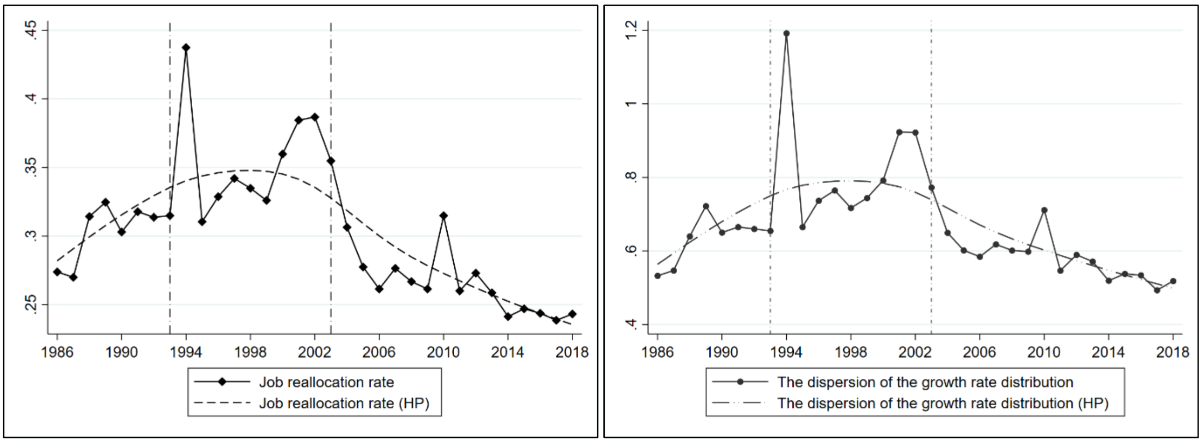

Figure 12. The structural breaks in job reallocation and growth rate dispersion

Note: The job reallocation rate is equal to the sum of the rates of job creation and job destruction. 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 firms. Trends are computed by applying a Hodrick-Prescott (HP) filter with a smoothing parameter of 100. Break dates are estimated using the Bai & Perron (1998) approach for unknown structural breaking point. Y axis does not start at zero.

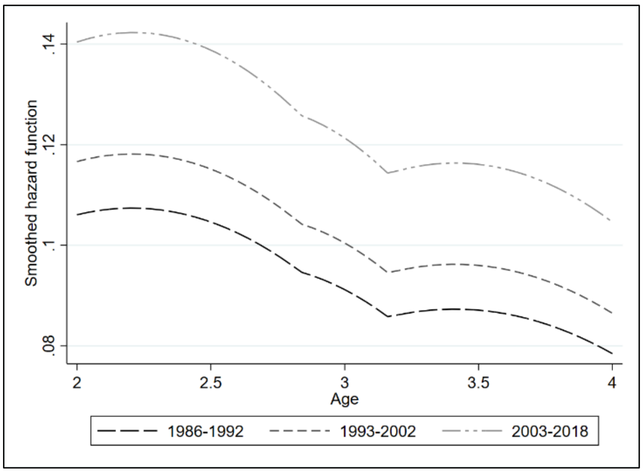

Figure 13. The hazard function of young firms by periods

Note: The graph shows the estimated hazard function of young firms for the periods 1986-1992, 1993-2002, and 2003-2018, conditional on the Cox-regression estimates. The hazard function reports the (limiting) probability of exiting the market in *t+1*, conditional upon the firm having survived in *t*.

7.2 Tables

Table 1—Bai & Perron (1998) estimation and test for structural breaks at unknown breakpoints

Estimation of break dates (H1: 2 breakpoints)					
Job reallocation					
Break number	Date	[95% Conf. Interval]		W(tau) statistic	p-value
1	1993	988	2998	845.28***	0.000
2	2003	1895	2111		
Dispersion of the growth rate distribution					
Break number	Date	[95% Conf. Interval]		W(tau) statistic	p-value
1	1993	1918	2068	473.54***	0.000
2	2003	1976	2030		

Notes: The Bai & Perron (1998) estimation approach for structural breaks at unknown breakpoints divides the sample at each possible breaking point. Then, it estimates the parameters using ordinary least squares, computing and storing the sum of squared errors. The least-squares estimate of the break date is the date that minimises the full-sample sum of the squared errors. Inferential statistics rely on a HAC covariance estimation. *** p<0.01, ** p<0.05, * p<0.1.

Table 2—Bai & Perron (1998) test for structural breaks at known break dates

Industrial dynamics indicator	*Break dates: 1993 and 2003*	
	W(tau) statistic	*p-value*
Job reallocation	845.28***	0.000
Dispersion of the growth rate distribution	473.54***	0.000
Job creation	701.75***	0.000
Job destruction	131.42***	0.000
Entry rate	888.52***	0.000
Exit rate	418.02***	0.000
Job creation by entrant firms	853.15***	0.000
Job destruction by exiting firms	163.60***	0.000
Skewness of the growth rate distribution	64.00***	0.000
HGFs (90th percentile)	654.83***	0.000
Share of new young firms in employment	342.91***	0.000
Net job creation by new and young firms	257.92***	0.000

Notes: Inferential statistics rely on a HAC covariance estimation. *** p<0.01, ** p<0.05, * p<0.1.

Table 3—Bai & Perron (1998) estimation and test for structural breaks at unknown breakpoints by sector

Estimation of break dates (H1: 2 breakpoints)					
Break number	Date	[95% Conf. Interval]		W(tau) statistic	p-value

Knowledge-intensive activities (KIA)					
Job reallocation					
1	1993	1918	2068	1401.30***	0.000
2	2004	1907	2101		
Dispersion of the growth rate distribution					
1	1993	1990	1996	494.90***	0.000
2	2003	1998	2008		
Non-knowledge-intensive activities (Non-KIA)					
Job reallocation					
1	1993	-463	4449	792.27***	0.000
2	2003	1900	2106		
Dispersion of the growth rate distribution					
1	1993	1705	2281	391.72***	0.000
2	2003	1968	2038		

Notes: The Bai & Perron (1998) estimation approach for structural breaks at unknown breakpoints divides the sample at each possible breaking point. Then, it estimates the parameters using ordinary least squares, computing and storing the sum of squared errors. The least-squares estimate of the break date is the date that minimises the full-sample sum of the squared errors. Inferential statistics rely on a HAC covariance estimation. Knowledge-intensive activities (KIA) are classified using the Eurostat methodology. Industries are defined on a time-consistent CAE Rev.2 basis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4—Bai & Perron (1998) test for structural breaks at known break dates by sector

Industrial dynamics indicator	***Knowledge-intensive activities (KIA)***		***Non-knowledge-intensive activities (Non-KIA)***	
	Break dates: 1993 and 2004		*Break dates: 1993 and 2003*	
	W(tau) statistic	*p-value*	*W(tau) statistic*	*p-value*
Job reallocation	1401.30***	0.000	792.27***	0.000
Dispersion of the growth rate distribution	727.91***	0.000	391.72***	0.000

Job creation	1039.83***	0.000	751.14***	0.000
Job destruction	162.57***	0.000	126.42***	0.000
Entry rate	807.18***	0.000	920.56***	0.000
Exit rate	271.92***	0.000	436.94***	0.000
Job creation by entrant firms	746.55***	0.000	817.25***	0.000
Job destruction by exiting firms	412.15***	0.000	141.80***	0.000
Skewness of the growth rate distribution	60.98***	0.000	63.44***	0.000
HGFs (90th percentile)	623.61**	0.000	662.17***	0.000
Share of new young firms in employment	449.06***	0.000	391.09***	0.000
Net job creation by new and young firms	703.87***	0.000	242.31***	0.000

Notes: Inferential statistics rely on a HAC covariance estimation. Knowledge-intensive activities (KIA) are classified using the Eurostat methodology. Industries are defined on a time-consistent CAE Rev.2 basis. *** p<0.01, ** p<0.05, * p<0.1.

Table 5—Regressions on the exit probability of young firms

	Cox regression	Logistic model
	(1)	(2)
VARIABLES	Hazard rate	Firm exit
1993-2002 versus 1986-1992	0.1021***	0.1182***
	(0.0065)	(0.0074)
2003-2018 versus 1986-1992	0.3031***	0.3584***
	(0.0062)	(0.0071)
Employment growth rate	-0.3719***	-0.3439***
	(0.0046)	(0.0056)
Ln (labour)	-0.4350***	-0.5117***
	(0.0024)	(0.0029)
Share of skilled workers in the labour force	-0.0917***	-0.1131***
	(0.0042)	(0.0052)
Age = 2		-0.4658***
		(0.0121)
Age = 3		-0.5484***
		(0.0122)
Age = 4		-0.6304***
		(0.0125)

Age = 5		-0.7038***
		(0.0128)
KIA sector dummy	-0.1302***	-0.1559***
	(0.0052)	(0.0062)
Business cycle	-1.6562***	-2.0243***
	(0.0483)	(0.0580)
Constant		-1.0754***
		(0.0134)
Location dummies	YES	YES
Observations	2,390,337	2,390,337

Notes: Cox-proportional hazard and logistic regressions on the exit probability of young firms. Young firms are less than five years. The periods were divided according to the structural breaks identified by Bai & Perron (1998) estimation procedure. (i.e., 1993 and 2003). The employment growth rate is computed using Davis et al.'s (1996) approach. Labour corresponds to the number of employees in the reference month. Skilled workers are those with high-school levels and above. The business cycle measure corresponds to the cyclical component of the region's annual net job creation rate. 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. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6—ATE and ATET of structural breaks on the exit probability of young firms born 1986 onwards

Survival regimes	Logit		Probit	
	ATE	ATET	ATE	ATET
(1993-2002 vs 1986-1992)	0.0190***	0.0183***	0.0191***	0.0185***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)
(2003-2018 vs 1986-1992)	0.0461***	0.0460***	0.0469***	0.0471***
	(0.0009)	(0.0008)	(0.0009)	(0.0008)
Potential outcome mean (1985-1992)	0.1062***	0.1049***	0.1058***	0.1047***
	(0.0009)	(0.0007)	(0.0008)	(0.0007)
Observations	2,390,337	2,390,337	2,390,337	2,390,337

Notes: Counterfactual model with multi-treatment levels. ATE and ATET are estimated by applying a regression adjustment model. The regression adjustment model uses contrasts of averages of treatment-specific predicted outcomes to estimate treatment effects. The binary outcome variable takes the value of 1 if the young firm exits the market in t + 1. The covariates for the outcome variable contain the log of initial size, the DHS firm growth rate, a dummy for knowledge-intensive activities, a business cycle measure (calculated as the cyclical component of net job creation by region), the share of skilled labour, and location dummies. Covariates were winsorised at the 1st and 99th percentiles. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.