Digital Technologies and Industrial Concentration
Are digital technologies fostering changes in industrial concentration?

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Statement of Integrity

I hereby declare having conducted this academic work with integrity.

I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

University of Minho, Braga, may 2024

Mickaël Esteves Da Cruz

Abstract

The relationship between competition and innovation is not new, but interest has resurged with the digitalization of the economies. While extensive literature has documented how digital technologies influence industrial concentration in regions like the US, Europe (as a group of countries), and individual countries from Europe, such as France or the UK, with evidence lacking from other countries. This dissertation investigates whether the recent industry concentration trends in Portugal are driven by the increasing adoption and use of digital technologies, contrasting with the mixed evidence observed across Europe and the pronounced effects in the US.

Utilizing two comprehensive panel datasets, SCIE and IUTIC-E, both from INE, which enable the computation of industrial concentration and digital technologies measures, this study employs OLS regressions to analyze the impact of digital technology adoption and use on changes in industry concentration from 2014 to 2022.

Findings indicate that despite a general downward trend in industry concentration in Portugal during the study period, higher levels of digital intensity and technology adoption are associated with increases in industrial concentration, as reflected in the CR20 and HHI indices. However, no very significant impact was found on the CR4 measure, suggesting that the average level of digitalization may not influence the largest firms in the same way, possibly due to their already dominant positions. This dissertation contributes to a nuanced understanding of how digitalization might influence industrial concentration in Portugal, and policymakers should guarantee that the adoption of digital technologies increase competion.

Keywords Aggregation, Digital Intensity, Digital Technologies, Digitalization, DII, Industrial Concentration

Resumo

A relação entre concorrência e inovação não é nova, mas o interesse ressurgiu com a digitalização das economias. Embora uma extensa literatura tenha documentado a forma como as tecnologias digitais influenciam a concentração industrial em regiões como os EUA, a Europa (como um grupo de países) e países individuais da Europa, como a França ou o Reino Unido, faltam evidências de outros países. Esta dissertação investiga se as recentes tendências de concentração industrial em Portugal são impulsionadas pela crescente adoção e utilização de tecnologias digitais, contrastando com a evidência mista observada em toda a Europa e os efeitos pronunciados nos EUA.

Utilizando dois conjuntos de dados de painel abrangentes, SCIE e IUTIC-E, ambos do INE, que permitem o cálculo de medidas de concentração industrial e de tecnologias digitais, este estudo recorre a regressões OLS para analisar o impacto da adoção e utilização de tecnologias digitais nas alterações da concentração industrial de 2014 a 2022.

Os resultados indicam que, apesar de uma tendência geral de redução da concentração industrial em Portugal durante o período de estudo, níveis mais elevados de intensidade digital e de adoção de tecnologia estão associados a aumentos da concentração industrial, tal como refletido nos índices CR20 e HHI. No entanto, não foi encontrado um impacto muito significativo na medida CR4, sugerindo que o nível médio de digitalização pode não influenciar as maiores empresas da mesma forma, possivelmente devido às suas posições já dominantes. Esta dissertação contribui para uma compreensão matizada de como a digitalização pode influenciar a concentração industrial em Portugal, e os decisores políticos devem garantir que a adoção de tecnologias digitais aumenta a concorrência.

Palavras-chave Agregação, Intensidade Digital, Tecnologias Digitais, Digitalização, DII, Concentração Industrial

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Acronyms

AI	Artificial Intelligence	1; 12; 20; 30; 42
CR4	Concentration Ratio of the top 4 firms	3; 8; 14; 15; 17; 18; 21; 23; 27; 28; 29; 36
CR20	Concentration Ratio of the top 20 firms	3; 14; 15; 17; 18; 21; 23; 27; 28; 29; 30; 36
DII	Digital Intensity Index	2; 20; 22; 23; 27; 29; 30; 35; 36
HHI	Herfindahl-Hirschman Index	3; 8; 14; 15; 16; 17; 21; 23; 27; 28; 29; 30 ; 36
INE	*Instituto Nacional de Estatística*	1; 2; 14; 19; 22
ICT	Information and Communication Technology	19; 20
IoT	Internet of Things	20; 42
IT	information technology	5; 6; 7;8; 9; 11; 13; 19; 28
IUTIC-E	*Inquérito à utilização de tecnologias de informação e comunicação nas empresas*	1; 2; 19; 20; 22; 30; 42
M&A	Mergers and Acquisitions	4; 5; 21; 29
OECD	Organisation for Economic Cooperation and Development	6; 7
OLS	Ordinary Least Squares	2; 27; 28; 40
R&D	Research and Development	5; 7; 10; 13
SCIE	*Sistema de Contas Integradas das Empresas*	2; 14; 15; 16; 20; 21
SMEs	Small Medium Enterprises	1; 23; 35; 36; 41
US	United States of America	2; 4; 5; 6; 7; 8; 9; 11; 12; 13;21

Chapter 1

Introduction

Since the beginning of the industrial revolution, the costs of making business across different locations have been diminishing [Autio et al., 2021]. Advances in the digitalization of the economies and diffusion of knowledge through globalization helped enlarge the benefits of innovation globally [International Monetary Fund Department, 2018]. Digital technologies can either help increase the power of the "top" firms or help smaller firms growing and catching up, leading to changes in industrial concentration. Depending on how digital technologies influence concentration the implications varies. For example, if increasing concentration is related to more market power it can slower innovation, decline business dynamism, and increase inequality [Brynjolfsson et al., 2023].

In Europe, the European Comission defined a programme to accelerate the transition to a digital economy until 2030. Some of the objectives, related to the digitalization of the firms are, for example, reaching a level where 75% of European firms use Cloud Computing, Artificial Intelligence (AI), or Big Data, and, related to late adopters, make more than 90% of Small Medium Enterprises (SMEs) reach at least a basic level of digital intensity. This second objective is particularly interesting as, in Portugal, according to *Instituto Nacional de Estatística* (INE), 99.9% of the firms are SMEs. In 2022, the Eurostat reported that 70.4% of the SMEs had reached the basic level of digital intensity, but only 4.1% with a very high level of digital intensity. This contrast with the values of the large business for 2022, where 97.3% had a basic level of digital intensity and 29.9% had a very high level of digital intensity.

Thus, the main objective of this dissertation is to explore the role of digital technologies on changes in industrial concentration in Portugal, using a survey for digital technologies such as the *Inquérito à utilização de tecnologias de informação e comunicação nas empresas* (IUTIC-E). Even though some literature has recently investigated the relation between competition and innovation [for example, Bajgar et al., 2023, Bessen, 2020, Brynjolfsson et al., 2023, De Ridder, 2024, Weiss, 2019], there is still a gap to be filled, which is related to specificities of digital technologies and their impact on industrial concentration. For instance, Autor et al. [2020] documented patterns of rising concentration that can be driven by the digitalization of the economies that lead to the creation of a "winner takes all" dynamic and the surge of superstar firms. But most of those evidences where mostly documented in the United States of America (US), lacking some evidence from other countries.

For Portugal, data on concentration was presented individually only in Bajgar et al. [2021][1]. Figure 3 from their work shows changes in concentration across countries compared to the base year 2002 based on the 8 largest firms by 2-digit industries[2]. In their study, Portugal shows a rise in concentration until 2014 of more than 10%, with a reduction in this change between 2013 and 2014. This is consistent with the recent findings of this work presented in Figure 3, in particular, that use data from the *Sistema de Contas Integradas das Empresas* (SCIE) between 2006-2022 and show a downward trend in sales national concentration between 2013-2020 (2022 for employment).

The use of Portuguese firm-level data give a new insight about this topic since the adoption of digital technologies and the process of digitalization is not homogenous across countries and industries [DeStefano et al., 2017]. Portugal is a country that since the beginning of the century suffer from low levels of growth and for that it is important to transform the productive profile of the economy to make it more competitive. Part of this transformation can be achieved with the adoption of digital technologies to create high value-added products and services which may have a multiplying effect on the economy. However, this process is different from country to country, and policymakers must have a well understanding of the environment firms are insert on to identify the best drivers of technology adoption and competition.

Therefore, this dissertation will try to answer whether a higher level of digital technology adoption is positively associated with changes in concentration. Moreover, It will also access the potencial impacts of higher digital intensity and the early impacts of some advanced digital technologies individually.

The use of the Portuguese firm-level panel datasets SCIE and IUTIC-E from the INE will allow to shed lights about the Portuguese reality on this subject. SCIE to compute concentration measures, and the IUTIC-E survey for the digitalization measures (the Digital Intensity Index (DII), the average level of adoption of advanced technologies, and a third measure which consist of analyzing the effects of some technologies individually). The research estimates Ordinary Least Squares (OLS) regressions using changes in industry concentration and tries to estimate the impact of several measures of digitalization. The findings reveal that despite the overall downward trend in industrial concentration in recent years, higher levels of digitalization and technology adoption are associated with positive changes in industrial concentration, particularly for

[1] But it does not mention Portugal in the text.

[2] The analysis covers manufacturing, construction and non-financial market services. Concentration increased in 68% of country-industries. Looking at weighted averages across industries, all countries experienced an increase in concentration. The weighting of sectors is important due to their varying significance within the economy over time. One of the cases is Spain, where the telecommunications sector gained a lot of importance, whereas the construction sector saw is weight in the overall Spain economy decrease.)

the concentration measures that corresponds to the concentration ratio of the top 20 firms (CR20) and Herfindahl-Hirschman Index (HHI). Interestingly, the measure of the concentration ratio of the top 4 firms (CR4) does not show strong statistical significant results, which might be explained by the fact that the technological measures are aggregated for the total industry. This suggests that the average level of digitalization may not significantly impact the largest firms at the top of the distribution, highlighting a nuanced response to digital adoption across different industry segments.

Besides offering new insights into concentration levels and technology adoption in the Portuguese economy, this research also contributes to understanding how digitalization may influence industrial concentration in Portugal.

The rest of this dissertation is organized as follows. Chapter 2 discusses relevant theories, the link between concentration and technologies, and the hypothesis; chapter 3 describes the data used and present the summary statistics ; chapter 4 present the methodology and the econometric results; and chapter 5 concludes.

Chapter 2

Literature Review and Hypothesis Development

2.1 Industrial Concentration: Background and Mechanisms

Before we dive into the relationship between concentration and technologies, it is important to understand how we can observe concentration in the economy, what could cause it, and what consequences it may have. In this analysis, concentration refers to a shrinking number of very large firms dominating employment and economic activity [Vollrath, 2019].

Several studies have documented an increasing in industrial concentration, with multiple explanations emerging for this pattern. For instance, Gutiérrez and Philippon [2017] attribute the rise in industrial concentration in the US to a decline in domestic competition and the lack of regulation. This second cause was latter explored by Gutierrez and Philippon [2022] who documented that the European Union made more efforts to increase competition (with the creation of the Single Market and independent European regulators) than the US and this translated to more accentuated decline in firm dynamics and competition in the US than in Europe. This situation can also be related to the difficulty in enforcing antitrust policies to address Mergers and Acquisitions (M&A). M&As have increasingly served as strategic tools for firms aiming to bolster their market positions and profitability by removing potential competitors, thus potentially altering industrial concentration. Theoretically, mergers can generate positive outcomes for firms by achieving economies of scale, improve efficiency or synergies, thereby enhancing operational efficiency [Grullon et al., 2019]. But they can also increase market power, and this effect become more dominant as the competition declines [Grullon et al., 2019].

In digital-intensive sectors, the term "killer acquisitions"[1] becomes relevant, describing scenarios where dominant firms acquire emerging startups that pose competitive threats [Bajgar et al., 2021].

[1] Cunningham et al. [2021] denoted "killer acquisitions", in the pharmaceutical industry, as incumbent firms purchasing innovative firms and discontinuing their projects to restrict technological progress and avoid future competition. The authors found that 6% of the acquisitions could match this classification, and despite the fact that this situation was only studied in the pharmaceutical sector, they argue that some of the implications can be extending to other industries as well, such as digital-intensive sectors.

Given that these practices frequently goes "under the radar", it is crucial for antitrust law enforcement to rigorously assess the effects of acquisitions on innovation and competition, because such strategic acquisitions tend to undermine competition and could hinder overall technological advancement [Cunningham et al., 2021].

Additionally, Akcigit and Ates [2021] link the increase in industrial concentration to a deceleration in technology diffusion from frontier firms to lagging firms, not only due to the lack of incentives to innovate but also because dominant firms end up purchasing potential new competition, consistent with the argument of weak antitrust enforcement of M&A leading to changes in industrial concentration [Bajgar et al., 2021, Cunningham et al., 2021, Gutiérrez and Philippon, 2017]. More recently Bessen [2022], elaborated on this situation, of a deceleration in technology diffusion, and points the complexity of new technologies and the reduced incentives for sharing[2], as underlying causes.

Competition based on complexity changes market and industry structures, enabling firms to differentiate themselves from their rivals. According to Sutton [1996], the strategic use of data allow firms to gain and sustain competitive advantages, as a higher level of R&D intensity tend to develop stronger market positions. The author also introduces the concept of alpha (α), an index that summarizes a firm's ability to leverage its Research and Development (R&D) and technology to impose a lower bound on market concentration. Firms with a high α are capable of maintaining dominance by disproportionately investing on R&D, thereby creating barriers to entry for potential competitors. This type of competition fosters "natural oligopolies" , where superstars firms dominate the industry.

The rise of superstar firms is one of the most compelling argument for the increase in concentration. Autor et al. [2020] argue that concentration reflects a rise of superstar firms driven by technologies, creating a productivity gap instead of a declining in competition. If globalization or technological changes increase the performance of the most productive firms (top of the distribution) in each industry, it will allow them to have a much faster increase in firm size and dominate the industry that they are inserted [Hsieh and Rossi-Hansberg, 2023, Autor et al., 2020]. This mechanism of superstar firms is consistent with the recent findings on local concentration. information technology (IT) advancements have reduced costs, enabling productive firms to expand locally, thus increasing their size and dominance [Brynjolfsson et al., 2008]. While the first results on local concentration in the US indicated an interesting paradox: national concentration was increasing, but competition at the local level was increasing [Rinz, 2022, Rossi-Hansberg et al., 2021], recent evidence indicates a rise in local sales concentration and a decrease in employment concentration [Autor et al., 2023, Hsieh and Rossi-Hansberg, 2023, Smith and Ocampo,

2 There is reduced incentives to share because that would reduce the level of differentiation of the dominant firms, and the complexity of the technologies difficult the capacity for the rivals to replicate them.

2022]. Relatedly, Aghion et al. [2023] suggest that the acceleration of IT innovations leads to decreased costs for firms to enter in more markets, thereby driving several economic phenomena, including decreasing local industrial concentration while rising national concentration.

In the context of the superstar mechanism and the digitalization of economies, Lashkari et al. [2018] finds that the rise in industry concentration in France from 1990 to 2007 can be attributed to a strong correlation between IT intensity and firm size. In this line, Bessen [2020] identifies a sectoral link between IT adoption and increased concentration, suggesting that digital technologies can enhance market power for adopting firms. Later, Brynjolfsson et al. [2023] also identified investment in IT as one of the main driving forces of increased market concentration. Aligned with this framework, Crouzet and Eberly [2019] observed that, since 2000, an increase in intangible capital among top public US firms is closely associated with rising industrial concentration, thereby leading to significant productivity gains and enhanced market power. Lastly, Chatterjee and Eyigungor [2023] attributes the decline in the startup rate and the subsequent increase in sales concentration among top firms to the decreasing risk-free rate, which enhances the profitability for larger firms to acquire new ideas from startups.

Although industry concentration is sometimes seen as a proxy for the degree of competition, an increase in concentration among larger firms does not necessarily imply an increase in market power. However, the results concerning concentration have been complemented by other proxies for market competition, and these are consistent with recent findings on markups and economic profits [Vollrath, 2019]. In their study, Gutierrez and Philippon [2022] conduct a comprehensive analysis of the evolution of various metrics related to concentration, including operating margins, profit shares, and Tobin's Q. Comparing the US to Europe, both regions have seen a decline in their investment relative to profits, a shift explained by a move towards intangible assets at the expense of physical investments. Firms in the US demonstrated higher operating margins and profitability, alongside a declining labor share and increased Tobin's Q. Firm-level analyses show increased profitability and mark-ups in the US, reflecting stronger pricing power and possibly limited competition [Gutierrez and Philippon, 2022].

Additionally, Calligaris et al. [2018] documented a rise in markups across 26 countries belonging to the Organisation for Economic Cooperation and Development (OECD), between 2001-2014. The rise in markups appear to be primarily driven by firms at the top of the distribution[3], and there are differences between digital-intensive sectors and less-digital-intensive sectors. Markups are notably higher in digital-intensive sectors, and the gap between these and less-digital-intensive sectors has widened substantially during the analyzed period [Calligaris et al., 2018]. De Ridder [2024] also found that the rise of intangible

[3] De Loecker et al. [2020] also present evidence of a higher increase in markups in firms at the top of the distribution. On the other hand, Hall [2018] find no evidence of markups being driven by mega-firm-intensive sectors.

inputs, such as IT and software, is associated to a rise in markups, not only in the US but also in France. As high-intangible firms gain in productivity, this increase is not transferred to wages; instead, it translates into higher markups [De Ridder, 2024].

Regarding firm dynamics, several authors have reported a decline in this metric [e.g, Aghion et al., 2023, Akcigit and Ates, 2021, Bajgar et al., 2023, Bessen, 2020, Chatterjee and Eyigungor, 2023, De Ridder, 2024, Hopenhayn et al., 2022]. Chatterjee and Eyigungor [2023] argue that part of this decline is due to firm's access to capital markets. The research underscores a positive correlation between business size and leverage, attributed to larger firms having more stable cash flows, enabling them to borrow more. Because of this, a lower risk-free rate makes it more profitable for larger firms to acquire innovative product ideas from startups, which lowers the startup rate. On the other hand, Hopenhayn et al. [2022] attribute part of the decline in entry rates to changes in population growth, that further translate in rising industrial concentration. More recently, emerging literature associates declines in firm dynamics with technological advancements [see, Bessen, 2020, Bajgar et al., 2023, De Ridder, 2024, for example]. Bajgar et al. [2023] also show that economies appear to be less dynamic, with declining entry and exit rates across most OECD countries. However, whether these findings indicate a reduction in competition or are a manifestation of competition in action remains unclear. De Ridder [2024] show that the overall rise in intangibles is accompanied by a decline in entry when firms becomes more efficient at using intangible inputs. The increase in R&D expenditures becomes less effective because it is concentrated among a small number of firms and because a fraction of innovators are unable to beat high-intangible incumbents.

In the US, a noticeable trend since the 1980s shows that a smaller number of large firms dominate employment and economic activity at a national level, encompassing both sales and employment [e.g, Aghion et al., 2023, Autor et al., 2020, Autor et al., 2023, Grullon et al., 2019, Gutierrez and Philippon, 2022, Kwon et al., 2023]. Brynjolfsson et al. [2023] have emphasized that this increase in concentration is more pronounced in sales than in employment, aligning with the earlier concept of scale without mass[4] developed by Brynjolfsson et al. [2008] and consistent with the findings of a decline in the labor shares documented by Autor et al. [2020].

While Gutierrez and Philippon [2022] document a rise in concentration beginning in the early 2000s, Kwon et al. [2023] extends this analysis further back, examining the long-term evolution of production concentration and demonstrating a rise over the past century from 1918 to 2018. However, this increase in concentration was not uniform over time. Examining the period from 1972 to 2014, Grullon et al.

[4] The scale without mass theory of digitalization suggests that through strategic investment in IT, firms can scale more easily and enhance both sales and productivity without proportionately increasing their workforce.

[2019] reports that competition levels in the US initially increased until 1996-97, which was then followed by a sharp increase in the HHI until 2014.

In Europe, the results are more ambiguous. In contrast to the US, Döttling et al. [2017] show stable or even declining levels of concentration in Europe between 1999 and post-2010[5], both for the HHI and the CR4 measures. Similarly, Cavalleri et al. [2019] reported a consistent level of industry concentration in the euro area from 2006 to 2015, albeit with some industries and countries differences. The top four firms represents between 10% and 20% of total sales, with higher concentration levels in the manufacturing sector, ranging from approximately 16% to 30%. Additionally Gutierrez and Philippon [2022] also do not show much evidence of growing concentration in Europe. In fact, they documented higher levels of competition in Europe, arguing that pro-competitive policies implemented since the beginning of the century, along with an independent European regulator, might have helped prevent a rise in concentration akin to that observed in the US [Gutierrez and Philippon, 2022].

Conversely, Bajgar et al. [2023], Bajgar et al. [2021] and Koltay et al. [2023] report a clear increase in industry concentration across Europe. Bajgar et al. [2023] documented a rise in concentration across 77% of 2-digit industries between 2000 and 2014, of about 4 percentage points, while Koltay et al. [2023] identified a concentration increase in 73% of industries for the combined industries of France, Germany, Italy, Spain, and the United Kingdom, between 1998-2019. This reflected in a rise in the average magnitude of concentration between 3.6 and 7 percentage points. Koltay et al. [2023] suggests that the differences observed in Europe concentration levels could be explained by the different methodological approaches used.

Several studies documented differences at the industry level in the trend of industrial concentration. Fostered by IT adoption Autor et al. [2020] documented an increase in concentration in the wholesale, retail, and service sectors in the US. Also in line with IT adoption across industries, Kwon et al. [2023], analyzing 100 years of US data on firm size distribution, shows that before 1970, the rise in concentration was stronger in the manufacturing and mining industries, and after 1970, it became more pronounced in services, retail, and wholesale.

During the period from 1998 to 2019, Koltay et al. [2023] identified an increase in concentration in the service sector, with the communication and transport and storage sectors witnessing the most significant growth. However, the hotels and restaurants sector did not exhibit an increase in concentration during this period. Regarding industry activities, transport-related industries exhibited the highest levels of concentration and the most substantial increases. Concurrently, digitally intensive industries demonstrated

[5] The authors don't mention the exact final year in their analysis.

an average increase in concentration, despite starting from a higher baseline in 1998.

Between 2001 and 2012, approximately 75% of 2-digit industries in Europe and North America experienced an increase in concentration [Bajgar et al., 2023]. Specifically, concentration measures revealed that the sales share held by the top 10% of firms increased by an average of 2 percentage points in manufacturing and 3 percentage points in non-financial market services. Moreover, the findings also show that their was a stronger increase in services in North America. Regarding employment, the share held by these top 10% firms, defined by their sales, increased in services but remained stable in manufacturing. This mirrors US trends indicating a shift from manufacturing to services. Finally, when differentiating between digital-intensive sectors[6] and less digital-intensive sectors, the same authors identified that the trends in concentration where not driven by digital intensive sectors and if for Europe the trends were similar for both type of sectors. In the US, less digital-intensive sectors exhibited a higher increase in concentration compared to digital-intensive sectors, despite digital-intensive sectors typically being more concentrated [Bajgar et al., 2023].

2.2 Digital Technologies: A Brief Overview and Relation with Competition

The evolution of digital technologies transforms how business is made, functions, and is structured. Thus, innovation can enhance competitiveness and drive productivity growth across various sectors, both horizontally and vertically [Cefis et al., 2023]. Recent studies point out gains in performance for firms that invest in new digital technologies [e.g, Acemoglu et al., 2018, Cefis et al., 2023, Cirillo et al., 2023, Forgione and Migliardo, 2023]. Other studies analysed the size of business [see, Brynjolfsson et al., 2023, Cirillo et al., 2023, Lashkari et al., 2018, for example], with Cirillo et al. [2023] suggesting that smaller firms benefit more rapidly from technology adoption, whereas larger firms take more time to notice the effect of the investment they have made.

However, the accumulation of IT combine with the high fixed costs associated to these technologies enables dominant firms to generate economies of scale [Brynjolfsson et al., 2023, Brynjolfsson et al., 2008]. Large firms benefit more than smaller firms as duplication of their business becomes cheaper, allowing them to enter in more markets (with new products or new locations), increase their performance, and have an overall larger firm size [e.g, Aghion et al., 2023, Brynjolfsson et al., 2023, Brynjolfsson et al., 2008], potentially leading to increased industrial concentration in the long run [Tambe and Hitt, 2012].

[6] Bajgar et al. defined digital-intensive sectors based on the taxonomy presented by Calvino et al. [2018].

This aligns with the previously mentioned superstar firms mechanisms from Autor et al. [2020], and with the notion that accelerating advancements in digital technologies reduce firms' market entry costs, thus contributing to various economic trends, including increased industrial concentration [Aghion et al., 2023].

Increased investments in intangibles are disproportionately benefiting larger firms, allowing them to grow and expand their market shares more efficiently. According to Bajgar et al. [2021], due to the scalable nature of intangibles, large firms are better positioned financially to invest in and leverage these assets across different markets. The authors also note that the impacts of intangible investments on industry concentration are amplified by the globalization and digitalization trends that the economies are undergoing [Bajgar et al., 2021].

The dominant effect of digital technology adoption can significantly influence employment trends. In the past, the substitution effect seemed to be dominating [see, Dewan and Min, 1997, for example]. Nowadays the dynamics are different with the adoption of digital technologies enhancing productivity and leading to the increase in revenues and employment within adopting firms [see Acemoglu et al., 2020, Bessen et al., 2020], while the industry or national-level evidence show a decline in overall employment, considering that non-adopting competitors have lower productivity, become less competitive and have had to significantly reduce their employment [Acemoglu and Restrepo, 2020, Acemoglu et al., 2020].

The digitalization of the economies is seen by several authors as influencing market power, markup, and industrial concentration [e.g, Autor et al., 2020, Bajgar et al., 2023, Babina et al., 2024, Bessen, 2020, Brynjolfsson et al., 2023, Calligaris et al., 2018, Crouzet and Eberly, 2019, De Ridder, 2024]. Indeed, the relationship between competition and innovation is well-established in economic literature. For instance, Romer [1990] argued that to have innovation, a certain level market power is necessary, as the resulting markups serve as the reward for the investment of time and effort in the innovation process. More recently, Aghion et al. [2005] find an inverted-U shape between product market competition and innovation, using patents as an indicator of innovation. When competition is too low, firms may lack the incentive to innovate, as they enjoy high profits without needing to invest in R&D. Conversely, when competition is too high, firms may struggle to recover their investment in innovation, as the potential rewards are quickly eroded by competitive pressures.

This suggests that the optimal patenting activity occurs within firms with intermediate levels of markups. Previous Industrial Organization models referred only a negative effect of product market competition on innovation with a reduction in postentry rents, and therefore reduces the equilibrium number of entrants [Salop, 1977, Dixit and Stiglitz, 1977].

2.3 Hypothesis Development

This study specifically relates to an emerging literature linking digital technologies to industrial concentration [e.g, Babina et al., 2024, Bajgar et al., 2023, Bessen, 2020, Brynjolfsson et al., 2023, Brynjolfsson et al., 2008, Weiss, 2019] fostered by the surge of "winner takes all" dynamics and superstar firms [Autor et al., 2020]. The observable trends of concentration across various countries and industries have increased interest in analyzing the potential effects of digitalization on industrial concentration. Bessen [2020] identified a positive link at the sector level between concentration and the adoption of IT. Additionally, Lashkari et al. [2018] also documented, for France, that the rise in industry concentration, between 1990 and 2007, coincided with an increase in IT adoption. Moreover, Babina et al. [2024] suggests that the use of artificial intelligence also contributes to the rise in industrial concentration.

Bajgar et al. [2021], analyzing the relationship between intangibles and industrial concentration across 13 countries from 2002-2014, found that changes in country-industry concentration are positively correlated with intangible investments, though this correlation was not observed with tangible investments. This contraries the findings of Gutiérrez and Philippon [2017] for the US economy.

An insightful perspective emerges from the research conducted by Brynjolfsson et al. [2023], indicating that firms with higher productivity, driven by the adoption of IT, not only increase their sales and employment but also enter in more markets. This support the idea that new technologies contribute to higher industry concentration in the long run [Brynjolfsson et al., 2023]. Therefore, the hypothesize states that:

Hypothesis 1 (Concentration): Digital technology adoption is positively associated with changes in concentration.

Advances in digital technology and intangible investments are at the center of the rise of superstar firms and increasing concentration [Autor et al., 2020, Covarrubias et al., 2020, Crouzet and Eberly, 2019, Bajgar et al., 2023]. With so many technologies available, an increasing number of firms are using them in bundles, with a hierarchy of increasing technological sophistication [e.g, Brynjolfsson et al., 2021, Cho et al., 2023, Andres et al., 2020], suggesting that the intensity of adoption may also play a role in concentration levels. For instance, Kwon et al. [2023] find that the timing and degree of increasing concentration in an industry are closely associated with an increase in technological intensity. The trade-off between fixed and variable costs is more beneficial, prompting firms to adopt new technology more intensively, which leads to a rise in industry concentration [Hsieh and Rossi-Hansberg, 2023]. Therefore, the following hypothesis addresses the intensity of technology adoption:

Hypothesis 2 (Intensity): Higher digital intensity is positively related to increased industrial concentration.

As the economy becomes increasingly digitized, interest has surged in the potential of data analytic and AI to emerge as significant general purpose technologies that promote economic growth and business value [Brynjolfsson et al., 2017]. Babina et al. [2024] show that larger firms increased their investments in AI during last decade and expand into more markets reinforcing the winner-take-most dynamics. In fact, AI appears to lower the high costs of product development for large firms [Akcigit and Kerr, 2018], allowing them to scale more easily.

However, there is a renewed expectation about the disruptive effect that Industry 4.0 technologies are having on the manufacturing and production process [Cefis et al., 2023]. Furman and Seamans [2019] identified significant rising trends in robotics and AI patenting that may have implications for the future growth of business dynamics in these industries. In Italy, Cirillo et al. [2023] analyzing the effects of new digital technologies on firm performance, found that firms more distant from the technological frontier during the pre-adoption period exhibited the most notable increases in production. This supports the argument that Industry 4.0 technologies have the potential to renew the productive capacity of an economy. Despite the improvements after adoption, it is important to maintain reasonable expectations given the limited diffusion of these advanced digital technologies [Cirillo et al., 2023]. For example, Benmelech and Zator [2022] suggest limited impacts of robots on firms, as they point to a small investment (less than 0.3% of aggregate expenditures on equipment) and firms being highly concentrated in a few industries. When they compare robots with more widespread digital technologies, the importance of the latter in firms' investment is significantly higher. This discussion give rise to a new hypothesis on advanced technologies:

Hypothesis 3 (Advanced technologies): The impact of advanced digital technologies on industrial concentration is limited.

Sectoral heterogeneity in concentration trends is evident [Autor et al., 2020, Bajgar et al., 2023, Koltay et al., 2023]. Exploring how digital technologies impact industrial concentration, based on sector-specific digital intensity, could provide policymakers a better understanding of the heterogeneous effects of digital technologies. When we look at the level of digital intensity within each industry, these disparities manifest primarily in the US, with less digital sectors demonstrating a more pronounced increase in concentration [Bajgar et al., 2023]. Consequently, if changes in digital intensity lead to increased concentration, sectors already characterized as digital-intensive would not be expected to exhibit a higher change in concentration compared to less digital-intensive sectors. Thus, the following hypothesis addresses differences between digital-intensive and less digital-intensive sectors:

Hypothesis 4 (Digital-Intensive Sectors): digital-intensive sectors exhibit smaller change in concentration compared to less digital-intensive sectors.

Finally, as we recall some of the objectives of the European Commission on the digitalization of the firms introduce in Chapter 1, it could be useful to understand how digital adoption and use by different business size could be influencing changes in industrial concentration.

Superstar firms are characterized by their unique ability to scale up innovations, and digital technologies have played a crucial role in their rise, driven by stronger economies of scale and network effects [Tambe et al., 2020]. Investment in IT translates into larger firm size, enables firms to replicate business processes with more production units, reach new markets and industries, and increase sales without proportionately increasing their workforce [Brynjolfsson et al., 2023, Brynjolfsson et al., 2008]. Large firms typically have greater resources to invest in R&D and IT, which are crucial for strengthening their market position and facilitate the creation of "natural oligopolies" [Sutton, 1996], leading to a situation where large firms can maintain or amplify their dominance [Aghion et al., 2023].

IT, together with the adoption of new management practices, has finally made it possible for firms outside of manufacturing to scale up production across a large number of locations [Hsieh and Rossi-Hansberg, 2023]. The diffusion of information systems such as Enterprise Resource Planning, inventory, accounting, and Human Resource management systems enables cost reductions through firm-wide information sharing and transfer [Brynjolfsson et al., 2023]. For instance, US firms in the service industries are expanding into more local markets. Employment, sales, and spending on fixed costs have increased rapidly in these industries, favoring top firms and leading to increased national concentration [Hsieh and Rossi-Hansberg, 2023]. IT seems to favor firms that can use it well rather than leveling the market, leading to increasing concentration [Bessen, 2020].

According to Brynjolfsson et al. [2023], higher IT intensity correlates with increased employment, but with a decline in the percentage change for large firms compared to small firms. This suggest, for employment measures, that increasing digital intensity for smaller firms could lead to more significant changes in employment concentration compared to larger firm, thereby leading to the formulation of the final hypothesis:

Hypothesis 5 (Large Firms): Higher digital intensity in Large Firms lead to smaller change in employment concentration compared to smaller firms.

Chapter 3

Data Sources and variables

3.1 Industrial Concentration

To measure concentration at an industry-level, several authors over the years have used different approaches. One of the most well-knowed measures of market concentration is the industry's HHI, but Aghion et al. [2005] reported some geographical and product market limitations of this index and used the Lerner Index instead. More recently, Autor et al. [2020] used three measures of concentration in their work[1]: the HHI and two concentration ratios based on the share of sales and employment that is capture by a specific number of the largest firms within an industry (CR4 and CR20). Accessing the dimension of the four largest firms in a industry can serve as an indicator of the competitive environment of those firms, as mentioned by Koltay et al. [2023]. Aghion et al. [2023] also use CR20 as one of the measures for concentration while Gutierrez and Philippon [2022] made a slight adjustment by using the CR8 instead. Looking at the top 10% of firms, for example, is also a possibility[2]. Using different metrics for concentration allows for a better understanding because it splits the weights differently among firms. For instance, Autor et al. [2020] observed a smaller increase in concentration for the HHI compared to the CR20.

In their work, Koltay et al. [2023] identified three conditions to be satisfied in order to have the appropriate concentration data: (i) the right level of aggregation, (ii) long enough time span, and (iii) coverage of the whole economy. The use of the panel dataset *Sistema de Contas Integradas das Empresas*, SCIE, for firm-specific characteristics, retrieved from the Portuguese National Institute of Statistic, INE, satisfies the aforementioned conditions. Available from 2006 to 2022, the SCIE allow to compute measures of industrial concentration at the CAE Rev. 3 industry up to a four-digit[3] level, as it is expected that a higher level of disaggregation is related to more competition between firms of the same industry [Bajgar et al.,

1 They initially calculate concentration measures for 4-digit industries, and subsequently, through a weighted average, reduced them into 6 main sectors.

2 According to Bajgar et al. [2023] the use of the HHI or the top 10% of firms may be unsuitable when firm coverage varies across industries or over time. Since the SCIE database gives an appropriate coverage of the firms from 2006, both measures can be used in the analysis.

3 Original SCIE database gives the industry at a five-digit level, albeit for consistency purposes the dissagregation in this study is limited to a four-digit level.

2023]. The database includes all firms[4] engaged in at least one activity of producing goods and/or services during the reference period across the entire country. firms primarily involved in agricultural production, financial activities, insurance, and non-market-oriented entities, including units of public administration and defense (except municipal services), mandatory social security, and various associative activities, are excluded from the scope [5].

Therefore, the concentration measures used are the HHI and also two concentration ratios (CR4 and CR20), as it enables for a more robust analysis based solely on employment, due the lack of a deflator for sales at industry-level. Since the SCIE is construct at the firm-level, It is necessary to compute the concentration metrics to estimate the link to digital technologies.

To compute the HHI, the methodology used is retrieved from the study of Autor et al. [2023]. Aggregated across four-digit sectors, industries are weighted by employment[6] for the period 2006-2022.

For each sector k, national (NAT) concentration is measure in year t for outcome E (Employment) as:

$$HHI_{kt}^{E,NAT} = \sum_{j \in k} w_{jt}^{E} HHI_{jt}^{E,NAT} \tag{3.1}$$

where $HHI_{E,j,t}^{NAT}$ is the Herfindahl Index in outcome E in industry j in year t, and the weight $w_{E,j,t}$ is the four-digit industry activity E share of industry j in sector k in time t. For example, the weight for industry j for the employment HHI is $w_{E,j,t} = \frac{E_{j,t}}{\sum_{j' \in k} E_{j',t}}$, where $E_{j,t}$ is the total employment of industry j at time t. The Herfindahl Index is the sum of squared 'market' shares for all firms in the relevant cell, multiplied by 100 for the scale to be the same as in the concentration ratios[7]. For example, in an industry j, the national employment HHI is:

The analysis based on the HHI in a given industry, for national sales, can be define as:

$$HHI_{jt}^{E,NAT} = 100 \times \sum_{i \in j} (S_{ijt}^{E})^2 \tag{3.2}$$

where $S_{ijt}^{E} = E_ijt/E_jt = E_ijt/\sum_i E_ijt$ is the employment share of firm i in industry j at time t.

Analogously, the economy wide concentration ratio is the weighted average of the average concentration in each sector:

$$HHI_{t}^{E,NAT} = \sum_{k} w_{kt}^{E} HHI_{kt}^{E,NAT} \tag{3.3}$$

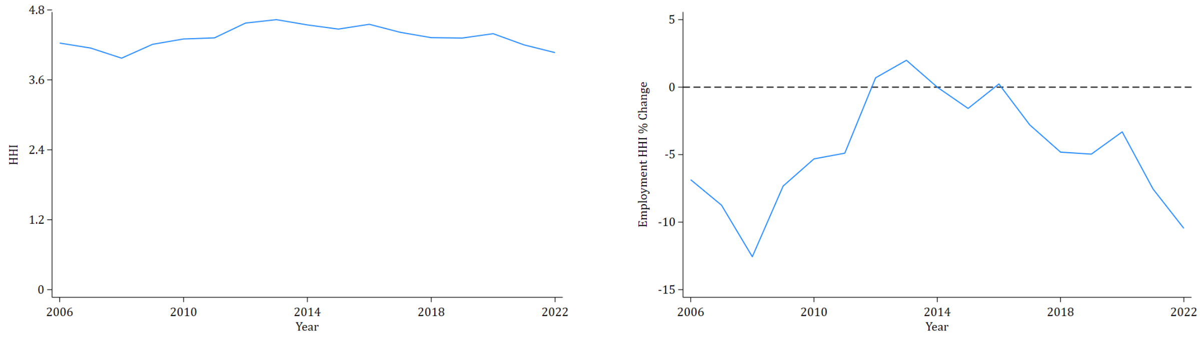
4 SCIE consider "firms" to be all firms, individual entrepreneurs and self-employed workers. Given this information, this dissertation only keep firms as the analysis of the digital technologies measures are only at the firm level.

5 See the methodological documents for additional information about the construction of this database.

6 Appendix A also compute the HHI for sales, and Autor et al. [2020] cleaning methodology, for some robustness in the results. All findings are consistent with the employment HHI measure.

7 A monopolist controls the entire market, 100 percent, resulting in a HHI of 10,000. Conversely, in a perfectly competitive market, the HHI is zero.

To ensure comparability across the different metrics, this study also show proportional changes in concentration relative to the baseline year 2014[8].



(a) National HHI

(b) % Change in relation to the baseline year 2014

Figure 1: National Employment HHI, 2006-2022.

Source: SCIE / Own Computations.

The national trend of concentration measured by the HHI (Figure 1) exhibit a stable level of concentration for employment from 2006 to 2022. However, when examining changes relative to 2014, a discernible decrease in the HHI, based on employment, is observed, exceeding 10% in 2022. Weighting the national HHI by industry employment provides a more accurate notion of concentration levels in Portugal as some sectors change their importance in the economy over the years. In fact, Figure 2 uses the percentage change in concentration in comparison to the baseline year 2014 by major sectors, and, in Sector D+E, concentration levels sharply decreased between 2007 and 2008, however with the weights the decrease became smoother in the national HHI, given that this sector only represented 1.82% of total employment[9]. Finally, Sector J, considered one of the most digitally intensive sectors, experienced an overall decrease in concentration between 2014 and 2022, despite the increase until 2019. In the eleven major sectors present in the figure, only four have a positive change in 2022 compared to 2014.

8 The empirical analysis only start in 2014, thus to understand how of different concentration measures behave over time the baseline year is established in 2014.

9 In this study, the term "total employment" is understood as the entire worforce in the firms that integrate the SCIE database.

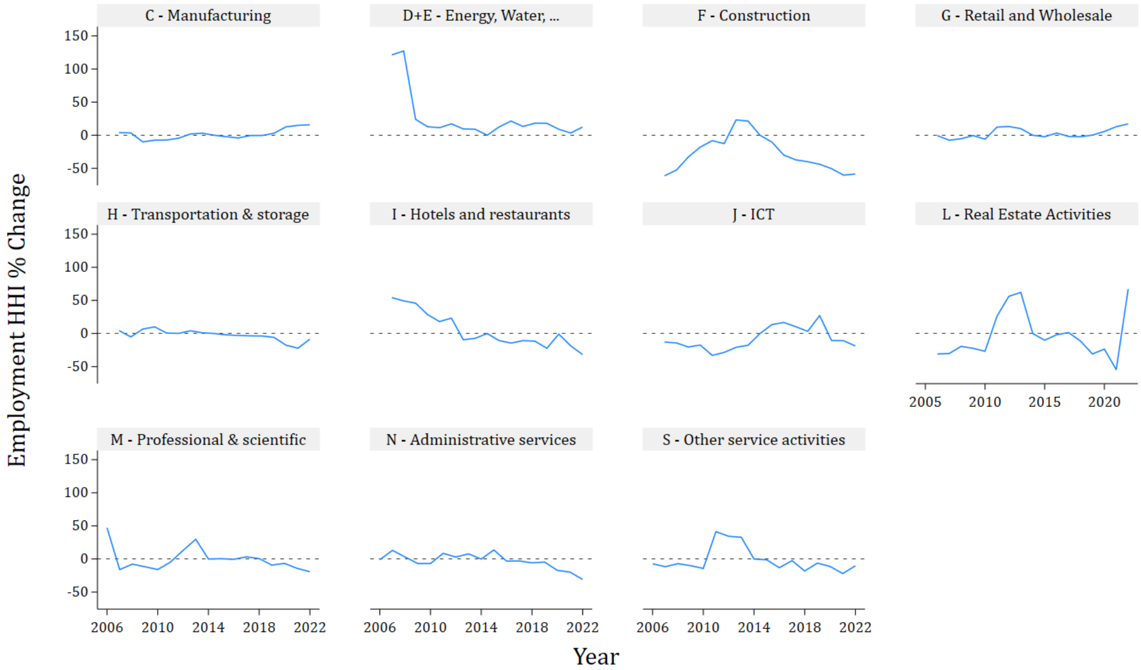


Figure 2: HHI % change in relation to the baseline year 2014 by major sectors - 2006-2022.

Source: SCIE / Own Computations.

As for the concentration ratios, the analysis is based on the share of industry for the outcome E (employment[10]) due to the $k \in \{4 \text{ or } 20\}$ largest firms in the industry can be define as in (3.4) as:

$$CR_k = \sum_{i=1}^{k} \frac{E_{ij}}{E_j} \tag{3.4}$$

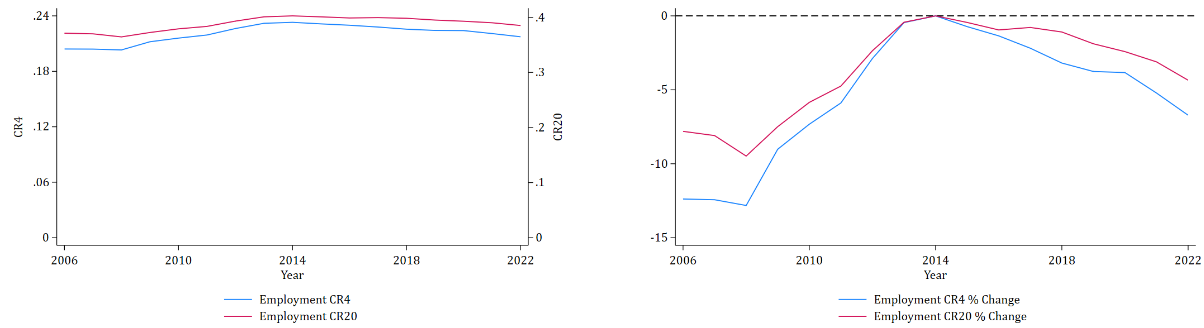
with i representing each of the top k firms in each j industry.

Figure 3 displays the national concentration ratios for the largest four firms (blue line) and the largest twenty firms (red line). These ratios are calculated for each four-digit CAE Rev.3 industry and subsequently averaged across all sectors within the national economy. The weighting of each industry is proportional to its employment share within each major sector and then the country. From 2006-2022, the CR4 and CR20 showed an increase in concentration. However, both measures experienced a decrease after 2014, presenting a similar pattern to the HHI.

Figure 4 displays the percentage change in concentration ratios compared to the baseline year 2014 across major sectors, and as for the HHI measure, sector J presents an overall decline in both measures between 2014 and 2022, although there was a small increase until 2019. Only sectors C and D+E had a consistent increase throughout the entire period in both measures of concentration, while sector G was the

[10] In a process similar to the HHI measure, appendix A present the concentration ratios computed for sales, and Autor et al. [2020] cleaning methodology. All findings remained stable, with the ratios starting to decrease in 2013.

only sector that experienced a positive change for CR4 and a negative change for CR20. But this situation does not necessarily imply less competition at the top of the distribution. For example, in Sector G, local grocery store, in the past, were present in almost each parish, but with the technological advancements (and "disruptive innovations") in the retail market, some chain stores started to increase their dominance in the market[11] and these small grocery shops began to disappear. However, within the chain stores, particularly in recent years, there appears to be increase in competition as these stores attempt to enter into more local markets, competing more locally.



(a) National CR

(b) % Change in relation to the baseline year 2014

Figure 3: National Employment Concentration Ratios, 2006-2022.

Source: SCIE / Own Computations.

[11] Consider, for instance, the case of Walmart in the United States. Bessen [2022] provide a comprehensive understanding on how this retail chain leverages technology to become dominant.

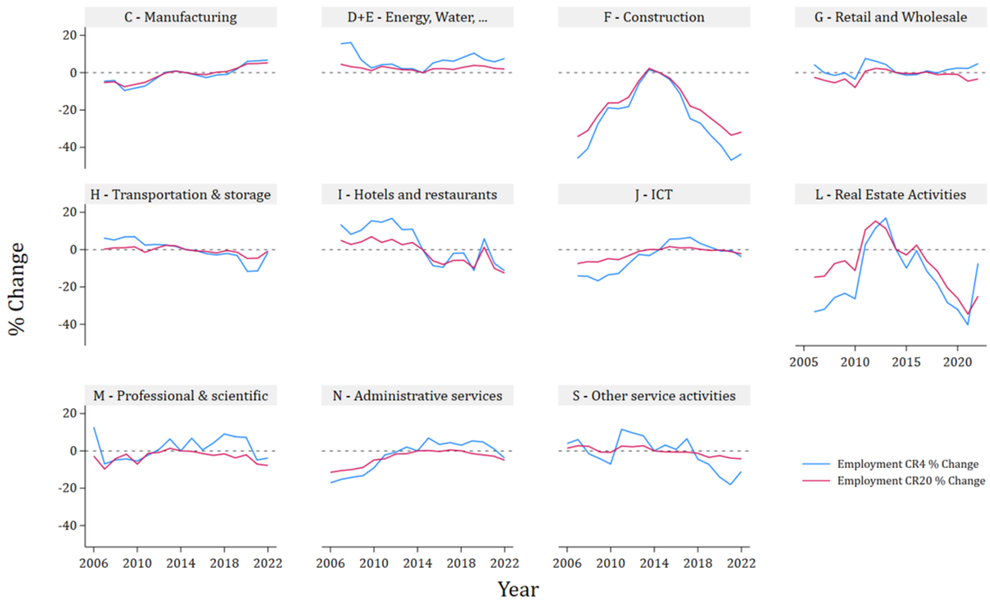


Figure 4: Concentration Ratios % change in relation to the baseline year 2014 by major sectors - 2006-2022.

Source: SCIE / Own Computations.

Finally, with this recent downward trend in the national concentration measures, it is important to determine whether digital technologies have positively influenced this decline or if the prevailing hypothesis that digital technology adoption increases changes in industrial concentration remains valid, and, thus, other market dynamics might be influencing this trend.

3.2 Digital Technologies

For the digital technologies measures, the study relies on another dataset from the INE, the *Inquérito à utilização de tecnologias de informação e comunicação nas empresas*, IUTIC-E, which is part of the Community Survey on Information and Communication Technology (ICT) Usage and E-Commerce and has been conducted annually since 2003. In Portugal, this survey functions as a census for large firms (those with more than 250 employees or turnover larger than 25 million euros) and as a stratified random sample for the other firms based on their size and industry affiliation. The survey is compulsory by law for certain firms, making it a reliable, rich, and valuable dataset. It also enables to measure the actual level of firm digitalization through specific technology-related questions instead of using solely expenses in IT, for example. The survey includes several questions related to digital technologies, from basic internet usage to more advanced technologies, such as cloud computing, robots, big data, artificial intelligence, or business information technologies. These questions have been intermittently included in the survey since 2014.

Even though it is a rich and reliable dataset for ICT measures, IUTIC-E is only representative at the aggregation-level[12]. In this study, the term aggregation refers to a group of economic activities retrieved from the NACE Rev.3 classification. To ensure reliability in the data, it was necessary to do this reduction in the number of economic activities, which is a limitation since it is not possible to disaggregate data at the four-digit level as in the SCIE database, thereby drastically reducing the number of observations.

Since this work seeks to estimate if digital technologies can be the cause for changes in the levels of industrial concentration, it is important to establish the empirical definition of "digital technology" and "digital intensity" used in this work.

Digital technology is based on the taxonomy elaborated by the European Commission and the AI diffuse project from Calvino and Fontanelli [2023], with the latter identifying several digital technologies. These technologies are categorized into advanced digital technologies (artificial intelligence, big data analysis, internet of things, machine learning, and 3-D printing) and of other digital tools or technologies (cloud computing, customer relationship management software, e-commerce, enterprise resource planning software, robots). Combining the information from the European Comission, Calvino and Fontanelli [2023], and the data available from the IUTIC-E surveys, the technologies considered are Cloud Computing; Big Data; Robots; and 3D printing[13].

The taxonomy for digital intensity rely on the Digital Intensity Index, DII, from the Eurostat. The DII is a composite indicator, derived from the survey on ICT usage and e-commerce in enterprises. The indicator includes 12 variables with each one having a score of 1 point. The DII distinguishes four levels of digital intensity for each enterprise: a count of 0 to 3 points indicate a very low level of digital intensity, 4 to 6 points indicates low level of digital intensity, 7 to 9 points indicate a high level of digital intensity and 10 to 12 points indicates a very high DII. The composition of the index varies between different years, depending on the questions included in each survey, hence to ensure some comparability over time the analysis only focus on the first version (v1) of the DII, available from 2014-2019.

[12] The IUTIC-E survey combine multiple two, three, and four digit industries into 32 main groups of economic activities (aggregations) to make it more easier to have representativeness. The composition of the Aggregation is present on Appendix B.

[13] Machine Learning; Internet of Things (IoT); and AI are not considered because this type of technologies only appear in the survey after 2019, while Enterprise Resource Planning and Customer Relationship Management are excluded to be considered technologies already widely spread in the economy.

3.3 Descriptive Statistics

Due to the differences in the number of observations and the technological variables used in the regressions to estimate the link between digital technologies and industrial concentration, the descriptive statistics presents 5 different tables. All tables present three measures of concentration (CR4, CR20, and HHI) and a 2-year change of these measures. For interpretation purposes, the absolute measures of concentration have been calibrated to range from 0 to 100. For instance, according to Table 1, the CR4 (the 4 largest firms of each four-digit industry of an aggregation) accounts, on average, for 19.93% of the employment within that aggregation, with the maximum value being 71.38%. As for the Change CR4, the mean tells us that, on average, a 2-year change during the period 2014-2022, reflected in a decrease of the level of concentration by -0.11% in the top four firms. The interpretation of the HHI and Change HHI follow Autor et al. [2023] study, where the upper bond of complete "monopoly" is scale to 100 instead of the 10.000 use by anti-trust practitioners. The scales remain equivalent but they differ in absolute levels. Thus, for Table 1 the HHI have values between 0.08 and 43.37 and the average change of the HHI was 0.38.

Additionally, using the SCIE database, the following set of control variables were calculated to be insert in the model: Net Entry, Δ Value Added, and log(Average Initial II).

Net Entry is a control for the supply of the industry, representing the net entry of firms in a 2-year period. The variable is scaled as a percentage, and thus, using Table 1 as an example, Net Entry increased by an average of 8.26%. In addition to account for the dynamics of entry and exit in the aggregation, this variable also serves to capture potential effects of M&A, which are occasionally cited as a potential cause for changes in industrial concentration [Bajgar et al., 2021]. As seen before, M&A can create positive outcomes like economies of scale and increased efficiency, but also boost market power, especially when competition diminishes [Grullon et al., 2019]. In digital-intensive sectors, this includes "killer acquisitions" where firms purchase startups to suppress innovation, which might reduce the entry of new firms [Cunningham et al., 2021, Akcigit and Ates, 2021, Bajgar et al., 2021, Gutiérrez and Philippon, 2017]. Therefore, the expected signal of Net Entry in the regressions is negative, as it is expected to slower down changes in industrial concentration.

Δ Value Added is a control variable for the demand of the aggregation representing the growth of the value added during a 2-year period. This variable is scale as a percentage, indicating that, according to Table 1, the average 2-year growth during the period under analysis was about 0.62%. Some findings in the US suggest that industries with a larger growth in real output also experienced a higher increase in concentration, mostly captured by superstars firms, but this situation does not necessarily imply weaker competition [Autor et al., 2020, Bessen, 2020]. Thereby, it is expected that the Δ Value Added will be positively associated with industrial concentration in the regressions.

And finally, log(Average Initial II) is another control variable representing the average initial log value of the investment in intangibles by the firms in each aggregation. Using the variable Average Initial II[14], we can better understand the level of investment across aggregations, with some investing as little as 165.44 euros per firms, according to Table 1, whereas other aggregations exhibit significantly higher investments reaching nearly 2.5 million euros.

This variable facilitates control over the size of investment across each aggregation, distinguishing between more digitally intensive sectors to less digitally intensive ones. As digital technologies need investments in intangibles to be used, largest firms benefit more from it as they have the resources to recover the "sunk costs" [Bajgar et al., 2021, Sutton, 1996]. However, the way this variable is constructed, as the initial average investment in intangibles, it suggests that for higher average investment, firms are closer to each other in the size of their investment, possibly generating more competition. Therefore, accounting for this situation and the positive link between other measures of intangibles and industrial concentration [see, Autor et al., 2020, Bajgar et al., 2021, Covarrubias et al., 2020, Crouzet and Eberly, 2019, De Ridder, 2024, for example], log(Average Initial II) could either be positive or negative depending on which effect is stronger.

As for the digital technology variables, in Table 1, Advanced Technologies represents the initial share of advanced technologies adopted by each aggregation. For instance, a value of 50 indicates that, for a given year, the aggregation adopted, on average[15], 50% of the available advanced digital technologies in the survey. For example, if four technologies were available in the 2018 survey, on average, firms in the aggregation adopted two technologies. From 2014 to 2022, the average adoption rate of Advanced Technologies in each aggregation was 14.87%.

In Table 2, the DII represents the level of digital intensity within each aggregation. The index can assume values from 0-12, where values above 4 indicate a basic level of digital intensity in the aggregation. The average across all the aggregations and years is above the basic level of digital intensity (4.12), yet half of the observations present in the sample do not reach this basic level. Appendix D presents more detailed data on the DII, where Figure 11 represent the level of DII by employment size class and year.

[14] Deflated using the Gross Domestic Product deflator from INE (baseline year = 2016).

[15] Given that the IUTIC-E database is a survey, the averages of digital technology variables were computed using weights to accurately reflect the broader reality. This study relied on weight of staff in service (POND_NPS) present in the IUTIC-E. Appendix C provides a detailed explanation of how the digital technology variables were constructed.

Three observations can be extracted from this figure. First, in Portugal, 99.9% of the firms are SMEs, which could explain the proximity between the line of the total index and the line for SMEs. Second, while digitalization is becoming more common, it is unevenly distributed, particularly skewed toward larger firms which typically have more resources to invest in technology, and third, it is visible the increase in digital intensity for the year 2019 compared to the previous years. It is unclear whether this is due to a national increase in digital intensity or change in the variables composing the index.

Additionally, Figure 12 from Appendix D illustrate the correlation between the DII and measures of industrial concentration (CR4, CR20, and HHI). The plots 12a and 12b show a moderate correlation (0.50 and 0.55, respectively) between the level of DII and the concentration ratios (CR4 and CR20). The third plot 12c, has a weaker positive correlation (0.30) between DII and HHI. Despite the positive correlation in all cases, this suggests a more modest association between digital intensity and overall industry concentration than with firms at the top of the distribution. However, this figure merely provides a snapshot of the current relationship, illustrating that more digitalized sectors tend to be more concentrated. It does not, however, explore the dynamic effects on concentration over time, making it premature to draw conclusions about the impact of increasing digital intensity on changes in concentration.

Finally, Table 3, 4, and 5 uses data of individual technologies separately. All variables were converted to assume values between 0-100 and they represent the % of adoption of the technology in the aggregation (a process identical to the variable advanced technologies). The intermittent availability of these technologies[16], poses challenges for continuous analysis and might affect the reliability of trends over time. The separation of data into different tables for each technology reflects this challenge and aims to provide a clearer picture of technology-specific adoption patterns.

[16] Big Data – 2016 and 2018; Cloud Computing – 2014, 2016, 2017, and 2018; 3D Printing and Robot – 2018.

Table 1: Summary Statistics Advanced Technologies - Aggregation-level

	count	mean	sd	min	p50	max
CR4	116	19.933	16.093	1.154	16.405	71.381
Change CR4	116	-0.106	2.418	-9.727	-0.174	9.935
CR20	116	35.902	23.130	2.742	29.390	85.522
Change CR20	116	-0.152	1.689	-4.398	-0.186	6.979
HHI	116	6.855	7.940	0.075	5.260	43.374
Change HHI	116	0.384	2.683	-13.954	-0.009	14.469
Advanced Technologies	116	14.867	11.530	1.361	11.575	59.818
Net Entry	116	8.261	8.465	-6.507	6.290	38.575
Δ Value Added	116	0.619	1.269	-8.030	0.701	2.459
Average Initial II	116	120 678.21	383 145.37	165.44	9 330.53	2 483 001.25
log(Average Initial II)	116	9.240	2.257	5.109	9.141	14.725

Notes: Summary statistics are based on the SCIE and IUTIC-E from 2014-2021, over a total of 29 Aggregations. However, since information on Advanced Technologies are not available for the year 2015 and 2019, periods 2016-2018 and 2020-2022 were excluded from the sample.

Table 2: Summary Statistics DII - Aggregation-level

	count	mean	sd	min	p50	max
CR4	168	20.218	16.560	1.154	16.721	71.381
Cange CR4	168	0.074	2.499	-9.727	-0.119	11.120
CR20	168	36.231	23.494	2.742	29.525	85.522
Cange CR20	168	-0.014	1.754	-5.232	-0.144	6.979
HHI	168	6.963	7.689	0.075	5.321	43.374
Change HHI	168	0.224	2.412	-13.954	-0.012	14.469
DII	168	4.124	1.876	1.346	3.720	8.891
Net Entry	168	7.118	7.912	-10.241	5.550	38.575
Δ Value Added	168	0.671	0.943	-5.862	0.685	2.479
Average Initial II	168	141 660.78	457 622.79	8.78	11 890.61	3 107 605.00
log(Average Initial II)	168	9.346	2.352	2.173	9.383	14.949

Notes: Summary statistics are based on the SCIE and IUTIC-E from 2014-2022, over a total of 28 Aggregations. To allow comparability, the data was restricted to the 1° version of the DII, only available from 2014-2019.

Table 3: Summary Statistics Cloud Computing - Aggregation-level

	count	mean	sd	min	p50	max
CR4	116	19.933	16.093	1.154	16.405	71.381
Change CR4	116	-0.106	2.418	-9.727	-0.174	9.935
CR20	116	35.902	23.130	2.742	29.390	85.522
Change CR20	116	-0.152	1.689	-4.398	-0.186	6.979
HHI	116	6.855	7.940	0.075	5.260	43.374
Change HHI	116	0.384	2.683	-13.954	-0.009	14.469
Cloud Computing	116	18.636	14.297	1.361	15.601	67.006
Net Entry	116	8.261	8.465	-6.507	6.290	38.575
Δ Value Added	116	0.619	1.269	-8.030	0.701	2.459
Average Initial II	116	120 678.21	383 145.37	165.44	9 330.53	2 483 001.25
log(Average Initial II)	116	9.240	2.257	5.109	9.141	14.725

Notes: Summary statistics are based on the SCIE and IUTIC-E for 2014-2021, over a total of 29 Aggregations, since data for cloud computing is only available for the years 2014, 2016, 2017, and 2018.

Table 4: Summary Statistics 3D Printing and Robots - Aggregation-level

	count	mean	sd	min	p50	max
CR4	29	19.763	16.462	1.154	16.247	60.658
Change CR4	29	-0.266	2.354	-8.195	-0.040	6.729
CR20	29	35.631	23.459	2.742	28.487	76.888
Change CR20	29	-0.373	1.498	-4.236	-0.248	2.071
HHI	29	7.082	8.134	0.075	5.358	34.264
Change HHI	29	0.270	3.796	-13.954	0.012	9.905
3D Printing	29	3.173	2.759	0.000	2.323	10.982
Robot	29	5.022	7.765	0.000	1.895	31.261
Net Entry	29	7.666	7.285	-6.507	7.955	23.854
Δ Value Added	29	-0.264	2.125	-8.030	0.130	2.459
Average Initial II	29	139 368.53	463 146.76	165.44	13 339.88	2 483 001.25
log(Average Initial II)	29	9.403	2.306	5.109	9.499	14.725

Notes: Summary statistics are based on the SCIE and IUTIC-E for 2018-2021, over a total of 29 Aggregations, since data for 3D Printing and Robot are only available for the year 2018.

Table 5: Summary Statistics Big Data - Aggregation-level

	count	mean	sd	min	p50	max
CR4	58	19.896	16.288	1.154	16.191	64.839
Change CR4	58	-0.082	2.559	-8.195	-0.122	9.935
CR20	58	35.817	23.255	2.742	28.970	81.124
Change CR20	58	-0.234	1.617	-4.398	-0.232	5.459
HHI	58	6.947	8.335	0.075	5.313	43.374
Change HHI	58	0.341	3.348	-13.954	-0.029	14.469
Big Data	58	11.370	6.764	2.537	8.665	31.479
Net Entry	58	8.274	8.350	-6.507	7.210	38.575
Δ Value Added	58	0.347	1.656	-8.030	0.553	2.459
Average Initial II	58	125 014.51	389 981.80	165.44	10 478.48	2 483 001.25
log(Average Initial II)	58	9.300	2.281	5.109	9.257	14.725

Notes: Summary statistics are based on the SCIE and IUTIC-E for 2016-2021, over a total of 29 Aggregations, since data for big data is only available for the years 2016 and 2018.

Chapter 4

Empirical Study

4.1 Methodology

To access the validity of the hypothesis, the study follows the approach of Autor et al. [2020], Bajgar et al. [2021], Bessen [2020], Brynjolfsson et al. [2023], examining the relationship between digital technology adoption and changes in industry concentration using estimate of OLS regressions based on the long differences approach (indicated by Δ). Long differences models are employed to analyze the effects of a variable over time, offering key insights into dynamic processes and long-term impacts. These models are particularly advantageous in scenarios where the effects of a variable, such as digital technology adoption on industrial concentration, may take time to manifest.

If we denote the variable of interest as Y, we can express the change in Y over time as:

$$\Delta^k Y_t = Y_t - Y_{t-k}$$

where the k represents the order difference of Y at time t, i.e, it represents the difference between the value of Y at time t and its value at a previous time period ($t - k$).

Adapting this specification to this study, we obtain the following model:

$$\Delta^k Concentration_{j,t} = \beta_0 + \beta_1 Tech_{j,t-1} + \beta_2 Z_{j,t-1} + \beta_3 \tau_t + \epsilon_{j,t}$$

Where for each industry j (at the aggregation-level) in year t, $\Delta^k Concentration_{j,t}$ indicates a 2-year change[1] in the industry concentration (e.g., HHI, CR4, and CR20) for the period 2014-2022. $Tech_{j,t-1}$ indicates the initial value of the technology measures (Digital Intensity Index (DII), the average level of adoption of Advanced Technologies, and individual technologies). The coefficient of interest in the equation is β_1, which indicates how the different measures of technologies contributes to a 2-year change

[1] Since the period of the data is very short (2014-2022), it is not possible to use long-term impacts and instead we rely on the specification of Bajgar et al. [2021] were the change corresponds only to a 2-year period.

in industry concentration. $Z_{j,t-1}$ indicates a set of control variables, τ_t is a full set of time dummies, and $\epsilon_{j,t}$ is an error term.

One of the major issues in studying the relationship between concentration and technology, is endogeneity, i.e, if the "direction of Causation" goes from digital technologies to concentration or vice-versa [Sutton, 1996], as another study before reported investments in IT as a possible endogenous variable [Bessen, 2020]. To address potential endogeneity concerns, particularly the issue of reverse causality, all independent variables are lagged by one-year. This lagging approach ensures that prior conditions are used as predictors, thereby reducing the likelihood that the observed changes in concentration could influence the observed levels of technology adoption in the same period. The use of the long differences model, despite the short-term variation, also might help mitigate the effects of endogeneity, as it reduces the probability to be expose to biased estimates from measurement errors Brynjolfsson and Hitt [2003], Greene [2017]. The model also allows for standard errors to be correlated over time by clustering at the aggregation-level.

4.2 Results

4.2.1 All firms and aggregations

In this section, Table 6 to Table 9 presents the results of the OLS regressions where the dependent variables are metrics of industrial concentration: CR4, CR20, and HHI. Time dummies are included, which helps account for any time-specific influences on the dependent variables, and the standard deviation is clustered at the aggregation level. The results are categorized based on the technological variable under analysis. Besides the individual t-tests present in the regressions and the robust standard errors to correct heteroscedasticity, this study also checks for some multicollinearity issues. Given the low levels of correlation between the digital technologies measures and the investment in intangibles, not more than 20%, and the low values for the VIF test, we proceed to the interpretation of the results.

According to Table 6, the average level of advanced technology adoption in the aggregation indicate a small but significant association with changes in employment concentration as measured by CR20 and HHI, while CR4 show no statistical significance. For instance, column 2 indicate that a 1 percentage point increase in the average adoption of advanced technologies should increase the change in concentration of the top 20 firms in each aggregation by 0.05 percentage points. The coefficient of Advanced Tehnologies in column 3 is similar to column 2, but slightly lower (0.03 instead of 0.05). This indicates that aggregation with a larger adoption of advanced technologies from 2015-2022 also experienced an increase in industrial concentration. This could suggest that firms which adopt advanced technologies gain competitive advantages that may increase their market share.

Although Advanced Technologies shows no statistical significance for the CR4 measure, it could be important to understand the potential reasons for this situation. One possible explanation is that M&A, common among firms at the top of the distribution, might overshadow the effects of technological adoption, particularly if we are in the presence of a "killer acquisitions" that slow down technology diffusion as dominant firms absorbs new competitors [Akcigit and Ates, 2021, Bajgar et al., 2021, Cunningham et al., 2021]. Additionally, top firms might not be significantly affected by average technology adoption, as they can leverage their dominant position, with established market presence and customer loyalty, for example, to maintain or enhance their market share regardless of broader industry trends.

Additionally, Net Entry is only statistically significant for CR20 at the 5% level. The negative signal suggests that increased net entry of firms is associated with lower changes in the CR20, likely because more firms enter in the market, promoting a more competitive environment. 2y ΔValue Added shows a significant positive association with CR4 and CR20, but not with HHI. This indicates that industries where value added is growing more tend to become more concentrated in terms of the largest firms growing larger, but this doesn't necessarily translate to the HHI measure of concentration. Finally, the relationship between Log(Average Initial II) and the concentration measures shows only a negative, statistically significant result for CR20 (at 10%). This could suggest that initial investments in intangibles do not consistently correlate with changes in concentration.

According to Table 7, the average level of digital intensity adoption within each aggregation shows significant association with changes in employment concentration across all measures. The significant results for DII across all concentration measures indicates that aggregations with a larger average level of digital intensity should experience a faster increase in industrial concentration in a 2-year period during the period of 2014 to 2022. This underscore the importance of digital adoption in shaping market structures. For instance, in column 1, a one point increase in the average level of digital intensity is associated with approximately a 0.49 percentage point increase in the employment CR4. Columns 2 and 3 show similar, but smaller, relationships for different measures. The results are statistically significant, with a 10 percent level for CR4 and a 5 percent level for both CR20 and HHI. This results, again, highlight the role of intensity in adoption and complementary between technologies, as DII is a composite indicator with different technologies, from the most basic to the most complex, and the results are statistically significant for all measures. The control variables Net Entry show a statistical significance for the CR20 measure, at 1%, and the Log(Average Initial II) for CR4 and CR20 measures at 10% and 5%, respectively. 2y ΔValue

Added show no significance at all.

Futhermore, Table 8 present the results on individual technologies, and the average level of individual technology adoption in the aggregation indicate only a significant association with changes in employment concentration for cloud computing in the CR20 and HHI measures. In column 5, for instance, a 10 percentage point increase in the average level of cloud computing adoption is associated with an approximately 0.37 percentage point increase in the 2-year change in CR20. Column 6 demonstrates a similar relationship for the HHI, with results for both CR20 and HHI being statistically significant at the 5 percent level. Column 5 and 6 show that the magnitude of the coeficient of cloud computing is very similar to the coefficient in Table 6, which can in part be explained by the fact that the variable Advanced Technologies is mostly composed by cloud computing.

The lack of statistical significance for other individual technology variables might, first, indicate a reduced number of observation for Big Data, 3D Printing, and Robots which prevents from estimate the impact of this technologies due to insufficient variability. Secondly, with so many technologies available, firms increasingly utilize them in bundles, with a hierarchy of increasing technological sophistication [e.g, Brynjolfsson et al., 2021, Cho et al., 2023, Andres et al., 2020], suggesting that the intensity of the adoption might also influence industrial concentration[2].

This notion of complementarity between different technologies, as reflected by the significant results for the variables Advanced Technologies and DII, underscores the potential for exploring interactions between individual technologies and the DII. This analysis, introduced in Table 9, provide similar results to the presented in Table 8. Additionally, when statistically significant Net Entry, ΔValue Added, and Log(Average Initial II) all present the expected signals.

The results for Table 6 to Table 9 allow to infer on the validity of the hypothesis from 1 to 3. Despite the negative trend in concentration, both Table 6 and Table 7 show that higher level of adoption of advanced technologies or digital intensity are positively associated with changes in industrial concentration, thus validating hypothesis 1. As for hypothesis 2, the result for the DII are statistically significant for all concentration measures, therefore this hypothesis seem also to be validate. But when we look to the third hypothesis, in particular to Table 8 and Table 9, the significant results for cloud computing contrast with the lack of significance for the other technologies studied. Since the reduced number of observations is appointed as one of the reasons that does not able to access the impact of advanced technologies individually and cloud computing show strong impacts when significant, it is not possible to validate this third hypothesis.

[2] Zolas et al. [2020] argue that to adopt AI technologies, firms need a huge amount of digital information (e.g, big data). For example, data from the IUTIC-E in 2020, reported that 33,7% of the firms use Machine Learning to analyze Big Data.

Table 6: Aggregation-level regressions of advanced technologies on change in concentration

	2-year changes		
	CR4	CR20	HHI
	(1)	(2)	(3)
Advanced Technologies	0.0487	0.0495*	0.0317**
	(0.0383)	(0.0246)	(0.0138)
Net Entry	-0.0369	-0.0718**	-0.0373
	(0.0336)	(0.0272)	(0.0304)
2y Δ Value Added	0.2935*	0.2286**	-0.0429
	(0.1464)	(0.0865)	(0.1978)
Log(Average Initial II)	-0.2631	-0.1851*	-0.0040
	(0.1624)	(0.1024)	(0.0648)
N	116	116	116
Clusters Aggregation	29	29	29
Time F.E.	YES	YES	YES
R^2	0.1142	0.2110	0.0392
Root MSE	2.3486	1.5482	2.7142

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of the **initial level of advanced technology adoption** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 29 aggregated industries. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively.Data is pooled from 2015–2022. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

Table 7: Aggregation-level regressions of DII on change in concentration

	2 year changes		
	CR4	CR20	HHI
	(1)	(2)	(3)
DII	0.4853*	0.3578**	0.2038**
	(0.2520)	(0.1350)	(0.0808)
Net Entry	-0.0344	-0.0616***	-0.0184
	(0.0307)	(0.0200)	(0.0283)
2y Δ Value Added	0.2078	0.1402	0.0254
	(0.1763)	(0.1039)	(0.2283)
Log(Average Initial II)	-0.2870*	-0.2193**	0.0025
	(0.1654)	(0.0982)	(0.1077)
N	168	168	168
Clusters Aggregation	28	28	28
Time F.E.	YES	YES	YES
R^2	0.1848	0.2365	0.0483
Root MSE	2.3199	1.5761	2.4195

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of the **initial average level of digital intensity index (v1) from Eurostat** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 28 aggregated industries. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2015–2022. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

Table 8: Aggregation-level regressions of individual technologies on change in concentration

	2-year changes											
	CR4	CR20	HHI	CR4	CR20	HHI	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Big Data	0.1459	0.0675	-0.1126									
	(0.1190)	(0.0569)	(0.1414)									
Cloud Computing				0.0447	0.0371**	0.0323**						
				(0.0402)	(0.0180)	(0.0121)						
Robots							0.0283	0.0050	0.1081			
							(0.0428)	(0.0279)	(0.1320)			
3D printing										0.0728	0.0198	0.1987
										(0.1546)	(0.0948)	(0.3510)
Net Entry	-0.0082	-0.0072*	0.0745	-0.0041	-0.0056	-0.0322	0.0032	0.0010	0.0448	0.0026	0.0009	0.0206
	(0.0066)	(0.0040)	(0.0856)	(0.0054)	(0.0036)	(0.0234)	(0.0036)	(0.0035)	(0.0485)	(0.0035)	(0.0033)	(0.0541)
2y Δ Value Added	0.0907	0.0633	0.1108	0.1935	0.1078	-0.1305	0.3263	0.2336*	0.1557	0.3208	0.2334*	0.1289
	(0.1458)	(0.1257)	(0.1100)	(0.1617)	(0.1134)	(0.1887)	(0.2017)	(0.1212)	(0.1108)	(0.2083)	(0.1185)	(0.1164)
Log(Average Initial II)	-0.4836**	-0.3140**	0.3086	-0.2837*	-0.1933**	-0.0091	-0.2532	-0.1896	-0.2724	-0.2495	-0.1911	-0.2261
	(0.2166)	(0.1337)	(0.2932)	(0.1592)	(0.0919)	(0.0676)	(0.1831)	(0.1200)	(0.2773)	(0.1917)	(0.1231)	(0.2895)
N	58	58	58	116	116	116	29	29	29	29	29	29
Clusters Aggregation	29	29	29	29	29	29	29	29	29	29	29	29
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.1894	0.2075	0.0482	0.1190	0.1498	0.0415	0.1020	0.1420	0.0310	0.1015	0.1427	0.0527
Root MSE	2.4126	1.5069	3.4197	2.3422	1.6072	2.7109	2.4094	1.4984	4.0365	2.4101	1.4978	3.9911

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of an **individual technology** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 29 aggregated industries. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2014–2021. Significance levels: *, 10%; **, 5%; ***, 1%.
Source: own computations.

Table 9: Aggregation-level regressions of individual technologies with DII on change in concentration

	2-year changes											
	CR4	CR20	HHI	CR4	CR20	HHI	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Big Data	0.0048	0.1019	-0.6200									
	(0.2265)	(0.1243)	(0.4412)									
BigData_DII	0.0288	0.0016	0.0722									
	(0.0247)	(0.0146)	(0.0437)									
Cloud Computing				-0.1588	-0.0479	0.0759						
				(0.1110)	(0.0609)	(0.1284)						
Cloud_DII				0.0290*	0.0131*	-0.0045						
				(0.0142)	(0.0071)	(0.0156)						
Robots							0.1745	0.0493	-0.0377			
							(0.2587)	(0.2038)	(0.5710)			
Robot_DII							-0.0605	-0.0221	0.0231			
							(0.0792)	(0.0582)	(0.1931)			
3D printing										-0.9416	-0.5346*	-1.0118
										(0.6106)	(0.2995)	(0.7579)
3D_DII										0.2467	0.1311	0.2965
										(0.1731)	(0.0867)	(0.2555)
Net Entry	-8.6818**	-6.8759***	4.7589	-4.0654	-5.0311**	-2.5696	-4.5102	-2.9510	-7.6190	-12.8102	-7.1204	-17.2118
	(4.1853)	(2.0092)	(6.3904)	(4.4268)	(2.2951)	(3.3723)	(4.3183)	(3.8068)	(9.5642)	(8.2788)	(4.2547)	(15.7882)
2y Δ Value Added	0.0847	0.2251*	-0.3840	0.1001	0.1472	-0.2279	0.3060	0.2796	0.0795	-0.0262	0.1144	-0.3372
	(0.1287)	(0.1270)	(0.3648)	(0.1848)	(0.1276)	(0.3221)	(0.3447)	(0.1747)	(0.1892)	(0.2439)	(0.1717)	(0.4418)
Log(Average Initial II)	-0.4833*	-0.3629**	0.4914	-0.1880	-0.1742*	-0.0821	-0.2086	-0.1608	-0.2926	-0.1789	-0.1441	-0.2423
	(0.2670)	(0.1464)	(0.3725)	(0.1949)	(0.0974)	(0.1400)	(0.1443)	(0.1098)	(0.3149)	(0.1687)	(0.1076)	(0.3170)
N	56	56	56	112	112	112	28	28	28	28	28	28
Clusters Aggregation	28	28	28	28	28	28	28	28	28	28	28	28
Time F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.2877	0.3151	0.1288	0.2182	0.2730	0.0500	0.1387	0.1838	0.0725	0.2434	0.2584	0.1385
Root MSE	2.3036	1.3915	3.3678	2.2224	1.4494	2.7589	2.4506	1.5195	4.1238	2.2968	1.4484	3.9743

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of an **individual technology and interaction with the DII** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 28 aggregated industries. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2014–2021. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

4.2.2 Robustness Checks

The results when we consider all firms and aggregations show positive effects of the technologies measures on changes in concentration. But understanding how digital technologies could be affecting industrial concentration depending on the type of sectors or firm size could give a more appropriate notion on the impacts.

Starting by the differences across sectors, the Chapter 2 show that digital technologies adoption and use might have different impact depending on the level of digital intensity of the sector. To investigate this situation, Table 10 present the results of aggregation-level regressions of DII for very high digital intensive aggregations and very low digital intensive aggregations[3] on change in concentration. The two groups present no statistical significance indicating that it is not possible, under this specification, to verify if it exist differences across sectors.

Since Table 10 makes the division of the level of intensity between observations, another robustness approach was used, drawing on the work of Barros and Nunes [2024], which identified six two-digit sectors to be part of the Portuguese digital industrial ecossystem (EID). This culminated in seven EID aggregations and 21 non-EID aggregations. The results, present in Table 11 show no particular differences between the two groups for the concentration measures, whereas the DII yelds a positive, statistically significant, result for non-EID aggregations, suggesting that increasing the level of DII in non-digital aggregations could have a more pronounced effect on the changes in concentration because the coefficient is higher than when we consider the entire sample (0.3283 and 0.2038, respectively). Therefore, although initial results indicated that hypothesis 4, pertaining to digitally intensive sectors, could not be validated, the final results suggest otherwise, rendering the findings inconclusive.

Additionally, and as it was mentioned before, Figure 11 from Appendix D, show that large firms have higher level of digital intensity, which are normally the firms at the top of the distribution. This higher level of digitalization could indicate that these firm leverage technology and the inherent fixed cost to assume a more dominant position within the sector and thus accelerate the increase in industrial concentration and explain the statistical significant result of the DII for the concentration ratios.

Thus, to explore this situation, Table 12, presents the results of the average DII, first for large firms and then for SMEs[4], on changes in industrial concentration. This table shows that if we consider only large firms to compute the DII, they do not present statistically significant results for the concentration ratios,

[3] The DII consider all values above 9 as a very high level of digital intensity, and values below 4 as very low digital intensity. Thus, the Very High DII group corresponds to all observations above 9 and the very low DII group corresponds to all observations below the level 4.

[4] The classification of Large Firms and SMEs is based on firm employment. Firms with 250 or more employees are considered large firms, while all others are classified as SMEs.

while the HHI present a significance at 5%, which might indicate that large firms have a higher influence when we consider a broader measure of industrial concentration. Concurrently, when we limit the measure of the DII to SMEs, the results indicate a clear increase in concentration in all measures, suggesting that SMEs can be creating more relative competitiveness changing firms positions and their market shares. Thus when SMEs increase there average level of digital intensity it lead to higher changes in employment concentration, which could be consistent with the results of Brynjolfsson et al. [2023]. Therefore, the lack of statistical significance for large firms contrast with the significance for SMEs, suggesting that hypothesis 5 might be accurate.

Finally, Figures 13 and 14 from Appendix E, display a 2-year disruption rate[5] in the CR4 and CR20, respectively, from 2006-2020, and, albeit a small increase in the measure when it captures the year of COVID-19, 2020, the figures how a stable and smooth decline in the disruption rate, suggest that the disruptive effects of digital technologies are not yet visible.

[5] This measure was adapted from the work of Bessen [2022], where the author uses a 4-year disruption rate for the four largest firms.

Table 10: Aggregation-level regressions of very high digital intensive and very low digital intensive aggregations on changes in concentration

	2-year changes					
	Very High DII			Very Low DII		
	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
DII	0.4764	0.0703	0.2487	0.0091	0.0179	0.6230
	(0.3752)	(0.3695)	(0.2670)	(0.1881)	(0.3175)	(0.4393)
Net Entry	-0.0498*	-0.0432*	0.0274	-0.0017	-0.0184	0.0055
	(0.0249)	(0.0242)	(0.0195)	(0.0170)	(0.0298)	(0.0222)
2y Δ Value Added	0.4253	0.1598	0.3064	-0.2216	-0.1790	-0.5628
	(0.3142)	(0.3035)	(0.2414)	(0.3427)	(0.6705)	(0.6808)
Log(Average Initial II)	-0.4174*	-0.3827**	-0.3148	-0.0370	-0.0476	-0.0986
	(0.2083)	(0.1458)	(0.2084)	(0.0558)	(0.0838)	(0.1446)
N	28	28	28	59	59	59
Clusters Aggregation	28	28	28	17	17	17
Time F.E.	YES	YES	YES	YES	YES	YES
R^2	0.3995	0.2961	0.3692	0.0526	0.0613	0.1886
Root MSE	2.0826	1.9835	1.4697	0.6229	0.9479	1.2625

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of the **initial average level of digital intensity index for very high digital intensive aggregations in the first three columns and very low digital intensive aggregations for columns 4,5, and 6** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 28 aggregated industries for very high digital intensity and 17 aggregated industries for very low digital intensity. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2015–2022. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

Table 11: Aggregation-level regressions of Digital Industrial Ecosystem and non-Digital Industrial Ecosystem on changes in concentration

	2-year changes					
	EID			non-EID		
	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
DII	-0.8875	-0.6260	0.1327	0.3708	0.2850	0.3283***
	(0.8974)	(0.5210)	(0.5330)	(0.2273)	(0.2058)	(0.1052)
Net Entry	-0.0972*	-0.0637**	-0.0154	-0.0255*	-0.0355**	-0.0266
	(0.0497)	(0.0243)	(0.0278)	(0.0125)	(0.0156)	(0.0240)
2y Δ Value Added	4.0956**	2.2214***	0.7119	0.1206	0.2416	0.1245
	(1.1356)	(0.3450)	(1.0917)	(0.1249)	(0.1454)	(0.1325)
Log(Average Initial II)	-0.5179	-0.4438***	0.0680	-0.1098**	-0.0922*	-0.0688
	(0.2921)	(0.1122)	(0.1976)	(0.0512)	(0.0465)	(0.0434)
N	42	42	42	126	126	126
Clusters Aggregation	7	7	7	21	21	21
Time F.E.	YES	YES	YES	YES	YES	YES
R^2	0.4375	0.5025	0.0851	0.2109	0.1274	0.1097
Root MSE	3.9234	2.2768	4.5720	0.9370	1.1244	1.3538

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of the **initial average level of digital intensity index for the portuguese Digital Industrial Ecosystem in the first three columns and non-Digital Industrial Ecosystem for columns 4,5, and 6** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 7 aggregated industries for EID and 21 aggregated industries for non-EID. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2015–2022. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

Table 12: Aggregation-level regressions of DII for large firms and SMEs on changes in concentration

	2-year changes					
	Large Firms			SMEs		
	CR4	CR20	HHI	CR4	CR20	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
DII	0.2379	0.1219	0.1924**	0.4396*	0.2790**	0.1817**
	(0.3188)	(0.1822)	(0.0735)	(0.2212)	(0.1215)	(0.0743)
Net Entry	-0.0439	-0.0296	(0.0735)	-0.0473	-0.0308	-0.0075
	(0.0391)	(0.0230)	(0.0109)	(0.0327)	(0.0201)	(0.0089)
2y Δ Value Added	0.6252**	0.3077**	0.0910	0.4272*	0.2462*	0.0472
	(0.3023)	(0.1335)	(0.2832)	(0.2380)	(0.1443)	(0.2731)
Log(Average Initial II)	-0.3400*	-0.2253*	0.0020	-0.3157*	-0.2311**	0.0028
	(0.1832)	(0.1147)	(0.0991)	(0.1697)	(0.1032)	(0.0923)
N	156	156	156	168	168	168
Clusters Aggregation	27	27	27	28	28	28
Time F.E.	YES	YES	YES	YES	YES	YES
R^2	0.1862	0.1684	0.0456	0.2279	0.2167	0.0469
Root MSE	2.4002	1.6064	2.5166	2.2579	1.5964	2.4213

Notes: Each cell displays the coefficient from a separate OLS aggregation-level regression of the **initial average level of digital intensity index for large firms in the first three columns and SMEs for columns 4,5, and 6** on time fixed effects and the change in the concentration measure (concentration ratio and HHI) indicated at the top of each column. Standard errors in parentheses are clustered by a set of 27 aggregated industries for large firms and 28 aggregated industries for SMEs. Net Entry, 2y Δ Value Added, and Log(Average Initial II) are control variables representing the net entry of firms in the period per the total number of firms at the begining of the period, a 2-year growth of the value added, and the average initial log value of investments in intangibles in the period, respectively. Data is pooled from 2015–2022. Significance levels: *, 10%; **, 5%; ***, 1%.

Source: own computations.

Chapter 5

Conclusion

5.1 Main findings

Worldwide economies are becoming more digitized, Portugal included. With the programme of the European Commision to accelerate the transition to a digital economy until 2030, it might be important to understand how this digitalization could be affecting and how it will affect some market dynamics, notably, industrial concentration, in Portugal.

Recent trends in industrial concentration show increased concentration in industries in the United States, while the evidence is mixed in Europe, with some countries showing similar trends and others showing more stable levels of concentration. Digital technologies tend to increase concentration and the fact that it enables dominant firms to leverage technological advancements, increasing productivity by entering in more markets as been appointed as one of the most dominant effects.

This dissertation has explored the relationship between digital technologies and industrial concentration, particularly within the context of Portugal from 2014 to 2022. By employing comprehensive panel datasets from Statistics Portugal and using OLS regression analyses, this study highlights significant interactions between digital technology adoption and industry concentration dynamics. This work also investigated the complementarity of digital technologies, using the intensity of adoption, and the early impacts of more advanced technologies.

This study starts by showing some stylized facts of the portuguese economy, such as the recent downward trend in national concentration in 2013/2014 until the least year available, 2022, and also some insights of the increase in digitalization from 2014 to 2019, with the adoption being skewed towards larger firms.

The first conclusion reveal that despite a general downward trend in industrial concentration from 2014 to 2022, a higher level of digital intensity or adoption of advanced technologies within aggregations are positively associated with changes in industrial concentration, consistent with the findings of other studies, for instance, the ones of Bessen [2020], Brynjolfsson et al. [2023], and Lashkari et al. [2018]. For Portugal, this means that it should exist other market dynamics offsetting the impact of digital technologies that lead to an overall decline in concentration.

This study also concludes that the digital intensity and the use of technologies in bundle enhance the impact on changes industrial concentration as the results are significant in all different measures of concentration. This also might suggest that if larger firms continue to be able to leverage the use of technology in the future despite the technological advancement in the other firms, specially SMEs, they might be able to increase their firm size and keep their dominance [Brynjolfsson et al., 2023, Lashkari et al., 2018].

As for the impact of the advanced technologies individually, the evidence is not so clear. It is not possible to infer on their changes in industrial concentration due to the lack of significance in the regressions. This is an important hypothesis specially if we expect these technologies to be disruptive, because the previous literature reported a deceleration of the technology diffusion from leading firm to followers and the complexity of the technologies as one of the motives [Akcigit and Ates, 2021, Bessen, 2022].

When we look at heterogeneous effects between different types of aggregations it is not possible to conclude, under this specification, that there is differences between digital intensive sectors and less digital intensive sectors. Therefore, this suggests that there might be other factors, such as market structure, regulation, or firm strategies, that could explain aggregation heterogeneity. Consequently, policymakers should consider other factors when assessing the concentration trends between sectors with different digital intensity.

5.2 Limitations and avenues for further research

The results might need further investigation but some insight could be given. The technological variables used are all averages, hiding the distribution level of technology across the firms. This implies that when we discuss a higher level of digital intensity, we do not know if the distribution of technology remained the same, i.e, skewed toward larger firms, or if smaller firms can be closing the gap. Thus, with Table 12 it is possible to see how a increase in different size class could by influencing changes in concentration, and the results suggest that, it is smaller firms that are fostering higher changes in concentration, since that, during the study period, only SMEs show that an increase in the average level of digital intensity consistently lead to higher changes in industrial concentration.

This study is not without its limitations. Starting by the construction of the data and the concentration measures, the incapacity to deflate sales at the industry-level for the entire period, limited the analysis only to concentration measures based on employment. After, because the IUTIC-E database is a survey, it was only possible to ensure representativeness when the data was at the aggregation-level, thus reducing considerably the number of observations. The reduced time-frame do not allow to estimate long-run impacts and the intermitent availability of some advanced technologies, cannot allow to study their impacts on changes in concentration, with some not being tested at all (AI, IoT, and Machine Learning).

Further research could expand on this work by first replicate the analysis for sales and see if we still have the same findings. Then it could explore the long-term effects of digital technologies on changes in industrial concentration with more data available. Furthermore, despite giving some insight on the relation between digital technologies and changes in industrial concentration, the result do not imply direct causality, thus, the model might need to take one step further in terms of identification strategy and introduce. Some steps were made to gauge potential endogeneity issues, but the use of Instrumental Variables (IV) could be a more robust approach to take into account. Given the significance of the variable cloud computing in the individual technologies regressions, future research could investigate the potential disruptive effect of advanced technologies and introduce new technologies in the analysis, such as AI, IoT, and Machine Learning, as data availability improves over time. This could help in understanding the nuanced effects of each technology on industrial concentration dynamics.

Another scope of analysis could focus on the good or bad implications of higher level of digital technologies leading to higher changes in industrial concentration. Industrial concentration can be efficient, if driven by price competition, intangible investments, and increased productivity among leading firms. Conversely, concentration might be inefficient, if it is characterized by diminished competition and increasing barriers to entry as incumbent firms become more entrenched [Covarrubias et al., 2020]. Thus, understanding the current implications these higher changes in concentration will be important for policymakers to make informed decisions.

This dissertation has shed light on the complex interplay between digitalization and industrial concentration in Portugal. As digital technologies continue to develop and spread in the economy, understanding their impacts on industrial concentration remains an area to be studied. Thus, this research contributes to laying the groundwork for future explorations into the digital economy's multifaceted impacts on market structures. In the current context of this analysis, digital technologies are not, are not reducing changes in industrial concentration, thus, if policymakers want to change this paradigm, they should encourage, not just more adoption by smaller firms, but the adoption of technologies that can increase competition.

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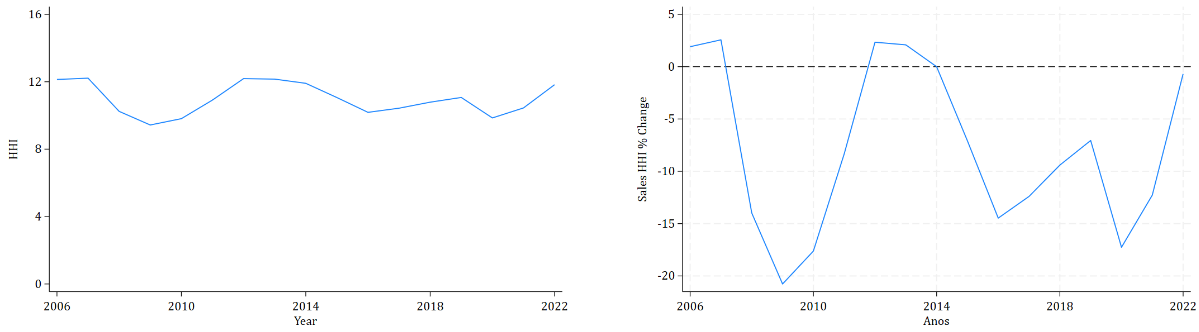
Part I
Appendices

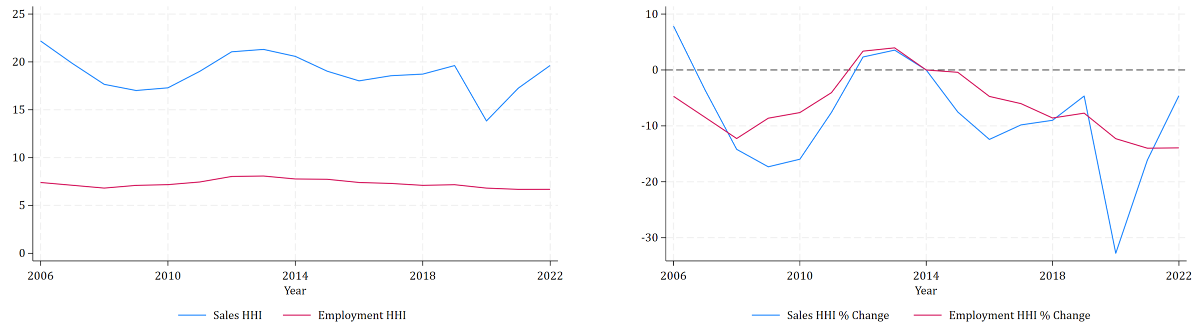
Appendix A
Concentration Metrics



(a) National Sales HHI

(b) % Change in relation to the baseline year 2014

Figure 5: National Sales HHI, 2006-2022.
Source: SCIE / Own Computations.



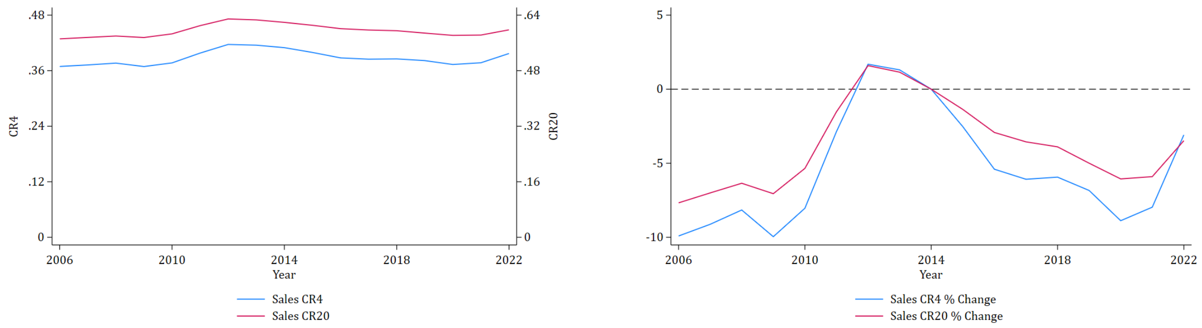
(a) National HHI

(b) % Change in relation to the baseline year 2014

Figure 6: National HHI, 2006-2022 - Autor et al. [2020] cleaning methodology.
Source: SCIE / Own Computations.

Despite the fluctuations, Figure 5 presents the results for the Sales HHI, with a downward trend in concentration between 2012 to 2020, with a sharp recovery after. Nevertheless, the overall change in concentration between 2014 and 2022 remains negative.

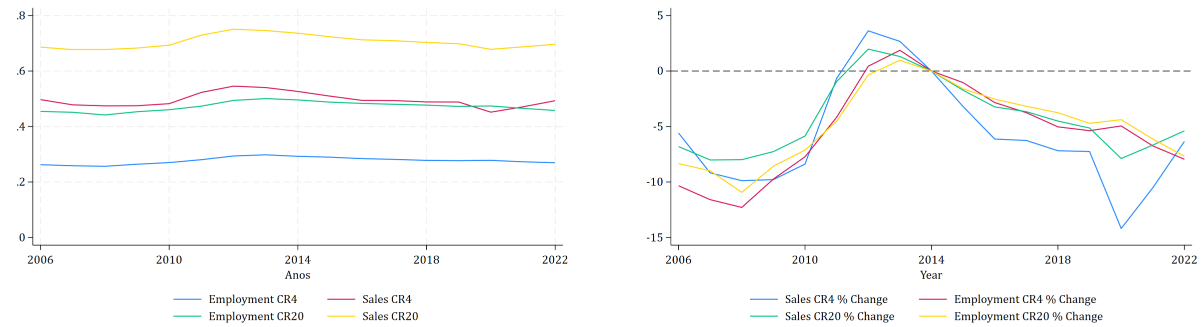
Additionally, the approach of Autor et al. [2020] for the cleaning of the data, keep only establishments that have at least one employee, a positive value of annual sales, value-added, assets, material costs, and salaries and wages. This type of cleaning doesn't seem to affect the observed trends in concentration, as Figure 6 now show a clear decrease of concentration not only for employment but also for sales using the year 2014 as our baseline.



(a) National Sales CR

(b) % Change in relation to the baseline year 2014

Figure 7: National Sales Concentration Ratios, 2006-2022.
Source: SCIE / Own Computations.



(a) National CR

(b) % Change in relation to the baseline year 2014

Figure 8: National Concentration Ratios, 2006-2022 - Autor et al. [2020] cleaning methodology.
Source: SCIE / Own Computations.

The concentration ratios for sales, in Figure 7, display a similar trend to the one found for the national sales HHI, i.e, we see an overall decrease in concentration after 2014, but with a small recovery after 2020.

Figure 8 show the Autor et al. [2020] approach for cleaning data and it reduce substantially the number of firms at the bottom of the distribution, giving the largest firms of each industry a higher rate of market concentration. Because of that, the industry become more concentrated at start, causing smaller changes in concentration over time, but the negative trend since 2014 is still present for employment and sales both the CR4 and CR20 measures.

Appendix B
IUTIC-E Aggregations

Figure 9 details the industries CAE Rev.3 that compose each aggregation.

		CAE Rev.3
Secção	Agregação	Niveis de classificação
C	agr01	10-12
	agr02	13-15
	agr03	16-18
	agr04	19-23
	agr05	24-25
	agr06	265
	agr07	266+267
	agr08	*2611+ 2612+ 2620+ 2630+ 2640+ 2680*
	agr09	27-28
	agr10	29-30
	agr11	31-33
D+E	agr12	35-39
F	agr13	41-43
G	agr14	45
	agr15	46 (*exceto : 4651; 4652*)
	agr16	4651+4652
	agr17	47
H	agr18	49-53
I	agr19	55
	agr20	561
	agr21	562+563
J	agr22	58-60 *(exceto: 5821;5829)*
	agr23	5821+5829
	agr24	61
	agr25	62
	agr26	63 *(exceto: 6311;6312)*
	agr27	6311+6312
L	agr28	68
M	agr29	69-74
N	agr30	77-78+80-82
	agr31	79
S	agr32	951

Figure 9: Aggregations - groups of economic activities
Source: *DOCUMENTO METODOLÓGICO - IUTIC-E 2018*

Appendix C
Construction of the digital technology variables

Advanced Technologies

Advanced Technologies represent the initial share of advanced technologies adopted by the aggregation. Thus, to compute this measure it is necessary to first identify the technological variables available in each year: Cloud Computing (2014, 2016, 2017, 2018); Big Data (2016, 2018); Robots (2018); and 3D printing (2018). Each technology assume the value 1 if the firm adopted the technology in that year. Then, all technolgies are sum generating the variable $bundle\_tech$, that consist on the number of techlogies that each firm adopted. But since the number of technologies can be different form survey to survey, a small transformation is necessary to allow for some comparability. This transformation consist in estimating the percentage of adoption by each firm, i.e, consider the year 2018, for the 4 technologies available in the survey of 2018, if a given firms adopted 2 technologies, it will have a percentage of adoption equal to 50. For that it is necessary to create a new varibale that count the number of technologies available in each year, max_tech:

$$max\_tech(year) = \begin{cases} 1 & \text{if } year = 2014 \\ 0 & \text{if } year = 2015 \\ 2 & \text{if } year = 2016 \\ 1 & \text{if } year = 2017 \\ 4 & \text{if } year = 2018 \\ 0 & \text{if } year = 2019 \end{cases}$$

Then the adjustment is made as follows:

$$advanced\_tech = \frac{bundle\_tech}{max\_tech} \times 100$$

Now that we have the rate of adoption at the firm-level, it is necessary to aggregate to our aggregation level. For that it is necessary to use the weight available in the IUTIC-E survey, since the firms in the survey represent other equivalent firms in the economy. The weight used is the *POND_NPS*, the weight of staff in service:

$$POND\_NPS_h = \frac{\sum_{i=1}^{N_h} X_{hi}}{\sum_{i=1}^{N_h} x_{hi}}$$

where N_h and n_h represent, respectively, the number of companies in the universe and in the sample of responses in the stratum h; X_{hi} and x_{hi}, designate the number of people employed by the company i in the universe and in the sample in the stratum h.

Now, we multiple this weight by the rate of adoption:

$$advanced\_tech\_weightedi, j = POND\_NPSi, j * advanced\_techi, j$$

Estimate the total level of technology adoption $total\_tech\_adoption$ and the total number of firms $total\_firms$ by year (j) and aggregation (k):

$$total\_tech\_adoption_{j,k} = \sum_{i=1}^{j}\sum_{i=1}^{k} advanced\_tech\_weighted_{i,j,k}$$

$$total\_firms_{j,k} = \sum_{i=1}^{j}\sum_{i=1}^{k} POND\_NPS_{i,j,k}$$

And then divide the total value of technology by the total value of the weight to obtain the average level of technology adoption in the aggregation:

$$\text{Advanced Technologies}_{j,k} = \frac{total\_tech\_adoption_{j,k}}{total\_firms_{j,k}}$$

Individual Technologies

Individual Technologies represent the initial share of an individual technology adopted by the aggregation.

This measure use the same technological variables as in Advanced Technologies: Cloud Computing (2014, 2016, 2017, 2018); Big Data (2016, 2018); Robots (2018); and 3D printing (2018). Each technology assume the value 1 if the firm adopted the technology in that year.

Then, all technologies were converted to assume values between 0-100 and they represent the % of adoption of the technology by each firm:

$$individual\_tech = individual\_tech \times 100$$

Now to obtain the value for the aggregation, we use the POND_NPS and multiple the weight by the rate of adoption in each firm:

$$individual\_tech\_weighted = POND\_NPS * individual\_tech$$

Estimate the total level of individual technology adoption $total\_tech\_adoption$ by year (j) and aggregation (k):

$$total\_tech\_adoption_{j,k} = \sum_{i=1}^{j} \sum_{i=1}^{k} individual\_tech\_weighted_{i,j,k}$$

and then divide the total value of technology by the total value of the weight to obtain the average level of each individual technology adoption in the aggregation:

$$\text{Individual Technologies}_{j,k} = \frac{total\_tech\_adoption_{j,k}}{total\_firms_{j,k}}$$

Digital Intensity Index

The Digital Intensity Index (DII) is a composite indicator, created by the Eurostat, derived from the IUTIC-E survey, that represents the level of digitalization of the firm. Since the composition of the index varies between different years (see Figure 10), the analysis only focus on the first version (v1) of the DII, that goes from 2015-2019. Because the question for the survey of 2015 are all present in the survey of 2014, the analysis also included the year 2014.

After computing the DII for each firm, the process from the firm-level to the aggregation level is similar to the used for Advanced Technologies and Individual technologies, using the $POND\_NPS$ as weight:

$$DII\_weighted = POND\_NPS * DII\_v1$$

Estimate the total level of DII $total\_DII$ by year (j) and aggregation (k):

$$total\_DII_{j,k} = \sum_{i=1}^{j} \sum_{i=1}^{k} DII\_weighted_{i,j,k}$$

and then divide the total value of DII by the total value of the weight to obtain the average level of DII in the aggregation:

$$\text{DII}_{j,k} = \frac{total\_DII_{j,k}}{total\_firms_{j,k}}$$

DIGITAL INTENSITY INDEX v1 (2015-2019)

The index is derived from the following features in:

Survey 2020: see DII v2

		2015	2016	2017	2018	2019
DI_INDEX	0-12	Give one point for each of the following 12 conditions, if true:				
		Enterprises where more than 50% of the persons employed used computers with access to the internet for business purposes	Enterprises where more than 50% of the persons employed used computers with access to the internet for business purposes	Enterprises where more than 50% of the persons employed used computers with access to the internet for business purposes	Enterprises where more than 50% of the persons employed used computers with access to the internet for business purposes	Enterprises where more than 50% of the persons employed used computers with access to the internet for business purposes
		Employ ICT specialists OR ICT functions are mainly performed by external suppliers	Employ ICT specialists OR ICT functions are mainly performed by external suppliers	Employ ICT specialists	Employ ICT specialists	Use at least 3 ICT security measures
		The maximum contracted download speed of the fastest internet connection is at least 30 Mb/s	The maximum contracted download speed of the fastest internet connection is at least 30 Mb/s	The maximum contracted download speed of the fastest internet connection is at least 30 Mb/s	The maximum contracted download speed of the fastest internet connection is at least 30 Mb/s	The maximum contracted download speed of the fastest internet connection is at least 30 Mb/s
		Provide more than 20% of the employed persons with a portable device that allows internet connection via mobile telephone networks for business purposes	Provide more than 20% of the employed persons with a portable device that allows internet connection via mobile telephone networks for business purposes	Provide more than 20% of the employed persons with a portable device that allows internet connection via mobile telephone networks for business purposes	Provide more than 20% of the employed persons with a portable device that allows internet connection via mobile telephone networks for business purposes	Provide more than 20% of the employed persons with a portable device that allows internet connection via mobile telephone networks for business purposes
		Have a website	Have a website	Have a website	Have a website	Enterprises make persons employed aware of their obligations in ICT security related issues
		Website has at least one of : description of goods or services, price lists; possibility for visitors to customise or design online goods or services; tracking or status of orders placed; personalised content int hewebsite for regular/ recurrent visitors	Website has at least one of : description of goods or services, price lists; possibility for visitors to customise or design online goods or services; tracking or status of orders placed; personalised content int hewebsite for regular/ recurrent visitors	Website has at least one of : description of goods or services, price lists; possibility for visitors to customise or design online goods or services; tracking or status of orders placed; personalised content in the website for regular/ recurrent visitors	Website has at least one of : description of goods or services, price lists; possibility for visitors to customise or design online goods or services; tracking or status of orders placed; personalised content in the website for regular/ recurrent visitors	Received electronic orders (web or EDI) from customers from other EU countries
		Use any social media	Use any social media	Use any social media	Website has links or references to the enterprise's social media profiles	Use any social media
		Have ERP software package to share information between different functional areas	Buy medium-high CC services	Have ERP software package to share information between different functional areas	Buy medium-high CC services	Have ERP software package to share information between different functional areas
		Have CRM	eInvoices sent B2BG, suitable for automated processing	Have CRM	eInvoices sent, suitable for automated processing	Have CRM
		Share SCM information electronically with suppliers or customers	Pay to advertise on the Internet	Share supply chain management information electronically with other enterprises, either suppliers or customers	Pay to advertise on the Internet	Use social media for at least two purposes
		Used any computer networks for sales (at least 1%)	Used any computer networks for sales (at least 1%)	Used any computer networks for sales (at least 1%)	Used any computer networks for sales (at least 1%)	Used any computer networks for sales (at least 1%)
		Enterprises where web sales are more than 1% of the total turnover and B2C web sales more than 10% of the web sales	Enterprises where web sales are more than 1% of the total turnover and B2C web sales more than 10% of the web sales	Enterprises where web sales are more than 1% of the total turnover and B2C web sales more than 10% of the web sales	Enterprises where web sales are more than 1% of the total turnover and B2C web sales more than 10% of the web sales	Enterprises where web sales are more than 1% of the total turnover and B2C web sales more than 10% of the web sales

e_di_vlo	Enterprise has very low digital intensity index	Count of enterprises with points between 0 and 3
e_di_lo	Enterprise has low digital intensity index	Count of enterprises with points between 4 and 6
e_di_hi	Enterprise has high digital intensity index	Count of enterprises with points between 7 and 9
e_di_vhi	Enterprise has very high digital intensity index	Count of enterprises with points between 10 and 12

Changes compared to previous year are in yellow

Figure 10: Digital Intensity Index v1.
Source: Eurostat

Appendix D

Digital Intensity Index

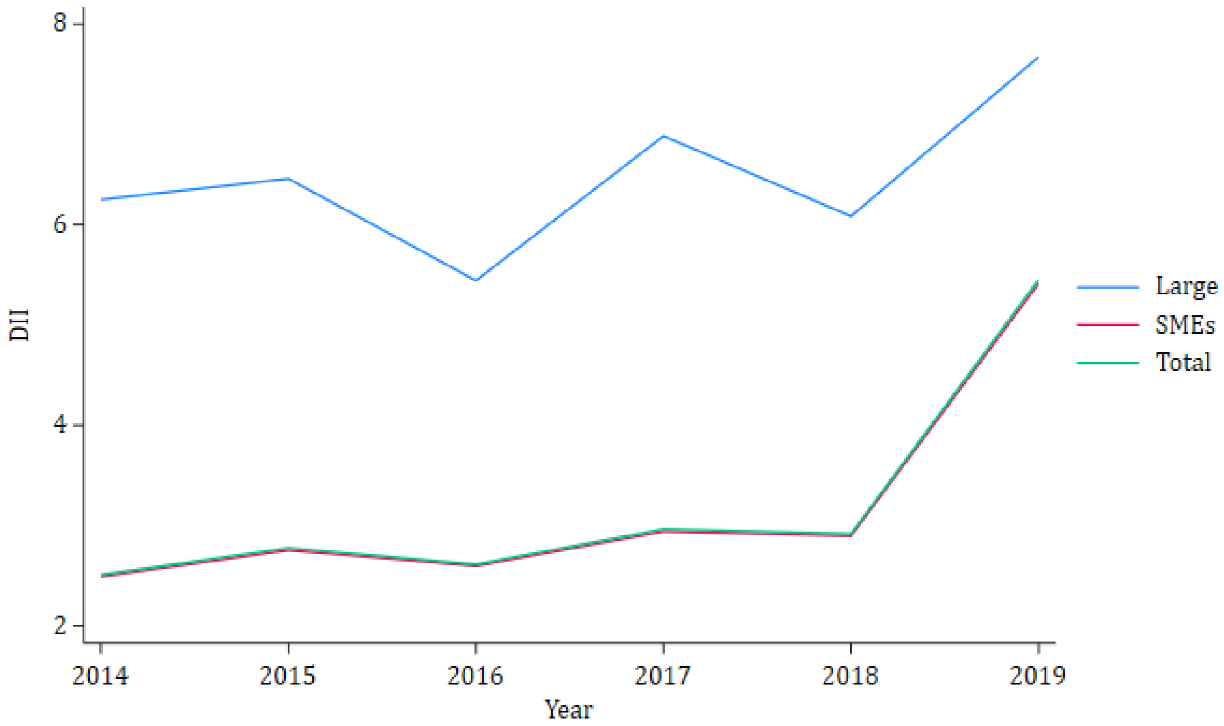
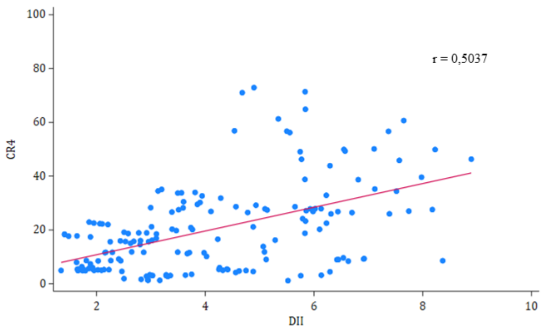
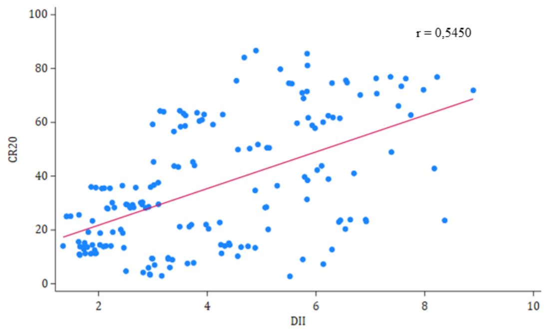


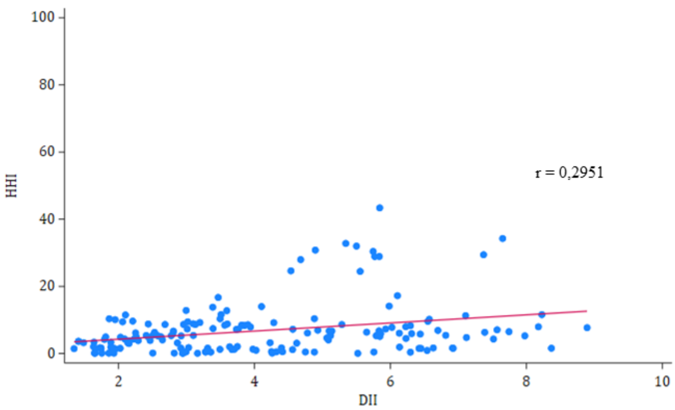
Figure 11: Digital Intensity Index (v1) by size class
Source: IUTIC-E / Own Computations.



(a) DII and CR4



(b) DII and CR20



(c) DII and HHI

Figure 12: Correlation between the level of digital intensity (DII) and the level of industrial concentration (CR4, CR20, and HHI).
Source: SCIE; IUTIC-E / Own Computations.

Appendix E
Disruption Rate

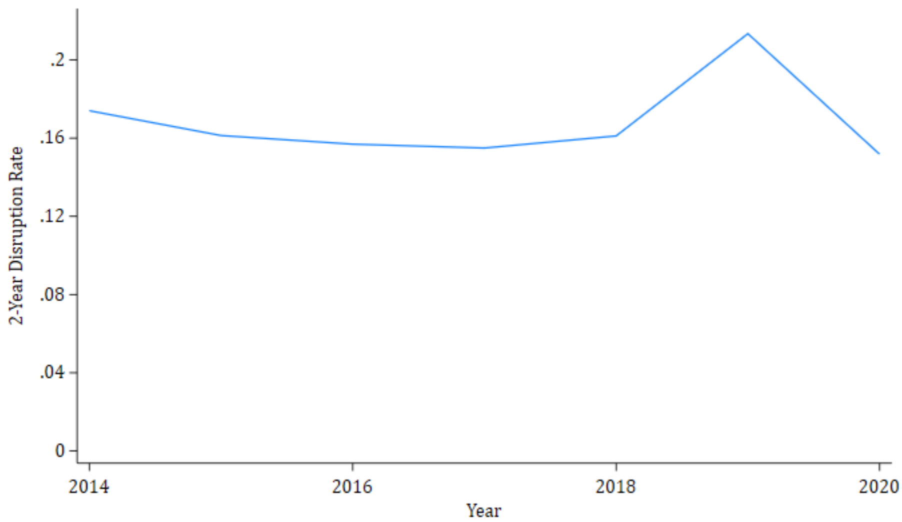


Figure 13: 2-year employment disruption rate for the CR4.
Source: SCIE / Own Computations.

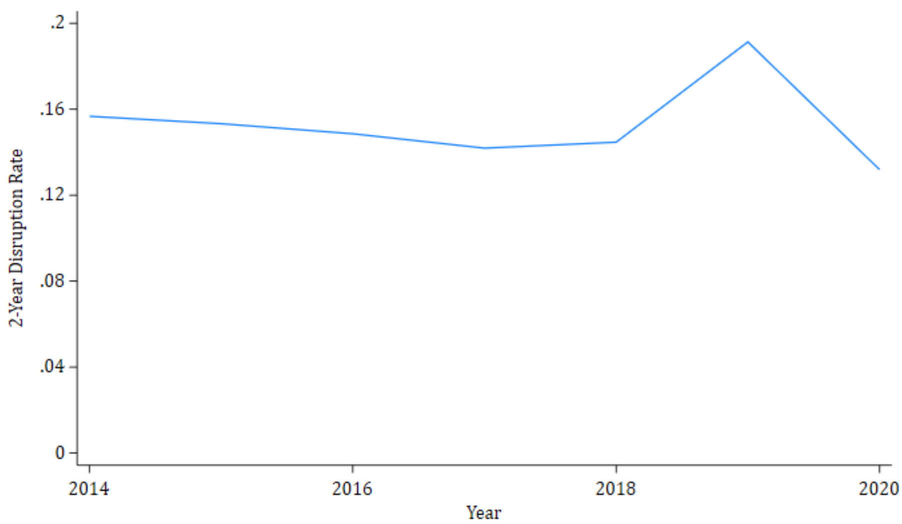


Figure 14: 2-year employment disruption rate for the CR20.
Source: SCIE / Own Computations.