Regional impacts of destructive and transformative digitalization on employment

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Abstract

We investigate the impacts of labor-saving and labor-augmenting digital technologies on employment at the municipality level in Portugal. We focus on the role played by agglomeration externalities from industrial diversity and labor specialization, employing occupation-level exposure measures by Frey and Osborne (2017) and Felten et al. (2021). We find that regions with both related and unrelated industrial variety have higher shares of workers at risk of being replaced by technology, as well as a greater exposure to the complementary effects of Artificial Intelligence (AI). Specialization in services decreases the vulnerability to the negative impacts of digitalization and enhances AI's benefits. In particular, knowledge intensity in services strongly decreases the share of employment at high risk of replacement, while promoting exposure to labor-friendly technologies. Our research provides insights for policymakers in smaller economies, emphasizing the need for region-specific strategies to navigate the technological landscape. A nuanced understanding of local labor markets is required for formulating effective policies to mitigate risks and harness the advantages of digitalization.

Keywords: digitalization; artificial intelligence; employment; regional labor markets; industrial diversity; knowledge intensity.

JEL Classification: R23, O33.

1 Introduction

The rise of new autonomous technologies involves critical implications for the macroeconomy (Eden and Gaggl, 2018; Basso and Jimeno, 2021) and the microeconomy (Sorgner, 2017; Fossen and Sorgner, 2021). Indeed, the rapid advancements in Artificial Intelligence (AI) and robotics present both significant opportunities and challenges for society (Raj and Seamans, 2018), implying the necessity of rethinking the organizational designs and firm strategies (Raj and Seamans, 2019). Given the complexity of the current technological change affecting the world economy at a multidimensional level, policy makers and researchers around the world are targeting, mapping, and investigating every aspect of the impact of new technologies in as much depth as possible.

The multilevel analysis of the impact of new technologies on jobs has led researchers to develop analyses at the task level, the occupation level, the sector level, the country level. At the task level, Manyika et al. (2017) state that more than 45% of tasks can be automated using current technology in industrialized countries. At the occupation level, some researchers have presented claim that 47 % of US jobs and 54% of European jobs are at high risk of computerization (Frey and Osborne, 2017; Bowles, 2014), while other authors have denied this alarmist vision of massive job destruction due to automation (e.g., Arntz et al., 2016, 2017; Lorenz et al., 2023). At the sector level, the literature has concluded that an increase in the robot-to-worker ratio promotes labor productivity growth (Graetz and Michaels, 2018) but also increases reshoring activity (Krenz et al., 2021), as well as reduces wages and the employment-to-population ratio (Acemoglu and Restrepo 2020a; Chiacchio et al., 2018). At the country level, literature confirms the continued technological leadership of the US, although this is declining in relative terms in favor of Asian countries (Santarelli et al., 2023). In addition to the *per se* complexity of the automation technologies employment impacts, the literature has revealed inconsistent and inconclusive results across various levels of analysis (Filippi et al., 2023).

Within all the multilevel analysis, the overall conclusion from previous studies is that the process of robotization varies by industry and country, suggesting that the impact of automation on human labor is not a one-size-fits-all scenario (Gentili et al., 2020). These findings highlight the necessity of specific regional analysis targeting the potential impact of autonomous technologies in distinct regions. A pioneering work developed by Crowley, Doran and McCann (2021) investigated the vulnerability of European regional labor markets to job automation, finding that regions with greater population density and unrelated variety were less vulnerable to automation.

Our paper contributes to the literature by assessing the potential implications of automation and AI for local labor markets, focusing on Portuguese municipalities. To develop our analysis, we leverage occupation-level measures on the probability of labor replacement by automation and exposure to labor-augmenting AI proposed by Frey and Osborne (2017) and Felten et al. (2021). In particular, we look into the role of agglomeration externalities in the form of related and unrelated variety, as well as labor market concentration and labor specialization. This analysis adds relevant information that can help Portuguese institutions, as well as those from other countries, navigate the technological wave by elaborating proper policies.

We find that both related and unrelated variety favor greater shares of workers at high risk of replacement by technology and at high exposure to the complementary effects. Regarding specific sectors composition, municipalities specializing in services seem to be protected from the destructive side of digitalization, while also relishing from a greater share of workers exposed to the benefits of AI. We also find that a higher share of college-educated workers strongly reduces the proportion of workers at high risk of replacement, while it positively increases the share of those with a high exposure to AI.

The rest of the paper is structured as follows. Section 2 presents a literature review and the main hypotheses. Section 3 details the data used. Section 4 depicts the empirical strategy. Section 5 offers the results and the discussion. Finally, section 6 summarizes the concluding remarks.

2 Literature review

The technological change encompassing the conglomerate of technologies of the *fourth industrial revolution* implies both old enhanced well-known processes in economic literature and new disruptive previously unknown technological paradigms. This *fourth industrial revolution* is defined as a fusion of technologies blurring the lines between the physical and digital spheres. Therefore, its associated process has been labelled as *digitalization*, defined as the transformation of business processes by leveraging digital technologies.

A robust body of literature has developed occupation-specific measures in order to build scores for the degree of exposure/suitability of occupations to technological advances. This literature is diverse, proposing and validating a variety of methodologies to understand the complexities of the digitalization process and its impacts. Concretely, measures have arisen for distinct technologies on Machine Learning (Brynjolfsson et al., 2018), AI (Felten et al., 2018; 2021; 2023), robotics (Webb, 2020) and computerization (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Montobbio et al., 2023).

The complexity of the conglomerate of technological innovations simultaneously going on has led researchers to consider the duality of digitalization divided among destructive and transformative effects as a simplification to help the understanding of the impacts of technological advances. Indeed, some authors considered that the new knowledge base of both digitalization sides is closely linked to the previous technological paradigm rather than representing a technological revolution, with robotics and AI converging to shape a new knowledge base that should be considered as a whole (Santarelli et al., 2023). The broad consensus in this literature is that digitalization and AI are transforming the occupational landscape, but the effects are not uniform across all jobs, industries, or regions. Furthermore, these transformations do not necessarily lead to job destruction but may lead to shifts in required skills and job tasks.

Computerization (computer-based automation) and robotization (robot-based automation) are the automation processes intrinsically going on within the technological revolution, constituting the so-called destructive side of digitalization. However, these are automation processes inherited from the third industrial revolution, which began in the middle of the last century, and are now being enhanced by the advancement of digital technologies. Indeed, the computerization process has implied a rapid skill upgrading since 1970 (Autor et al., 1998) with computer capital substituting workers in performing cognitive and manual tasks while complementing workers in nonroutine problem-solving and complex communications tasks (Autor et al., 2003).

AI is likely to be the technological innovation gaining the greatest attention in the digitalization process. On the one hand, AI will affect all occupations to different extents (Acemoglu and Restrepo, 2018a), outperforming humans in many activities in the following years (Grace et al., 2018), with jobs not affected by previous waves of automation now subject to high AI exposure (Tolan et al., 2021). On the other hand, literature has documented the current labor-friendly side of AI with AI-related job vacancies rapidly growing (Acemoglu et al., 2022), AI skills demand increasing (Alekseeva et al., 2021), AI patents having a positive and significant impact in employment (Damioli et al., 2023), and AI technology being positively associated with productivity and employment (Yang, 2022). This AI labor-friendly side has led some researchers to label AI as the transformative side of digitalization (Fossen and Sorgner, 2019).

2.1 Occupation-level measures for digitalization

Frey and Osborne (2017) presented an early innovative method, estimating the probability of computerization for various occupations to predict future computerization impacts on the US labor market. They provided significant insights into the number of jobs at risk, and the correlation between an occupation's probability of computerization, wages, and educational attainment.

A parallel line of research has focused on understanding the impact of AI on occupations. Felten et al. (2018, 2021) proposed methodologies to link AI advances to occupational abilities and developed a measure named AI Occupational Exposure (AIOE). This measure was used to create AI Industry Exposure (AIIE) and AI Geographic Exposure (AIGE) metrics, providing insightful data about how occupational descriptions have changed due to AI advances and exposure. Later in 2023, Felten et al. expanded their research, showing how AI advances in language modeling, like Generative Pre-trained Transformer (GPT) models, can significantly impact certain occupations and industries, including telemarketers, post-secondary teachers, and sectors such as legal services and securities, commodities, and investments. Eloundou et al. (2023) show that approximately 80% of the U.S. workforce could have at least 10% of their work tasks affected by the introduction of GPTs, while 19% of workers may see at least 50% of their tasks impacted. In this line, Floridi and Chiriatti (2020) highlight that readers and consumers of texts will have to get used to not knowing whether the source is artificial or human.

Likewise, Webb (2020) offered a fresh perspective on predicting technology's effects on occupations, focusing on the intersection of job tasks and patent texts. In contrast to previous assumptions about AI focusing on low-skilled tasks, Webb's research suggested that AI may actually be directed at high-skilled tasks, potentially reducing wage inequality. The potential of Machine Learning (ML) has also been an important topic. Brynjolfsson et al. (2018) discussed the transformative potential of ML for occupations and industries, devising a measure called "Suitability for Machine Learning" (SML). They discovered that although most occupations incorporate some SML tasks, very few are entirely automatable.

Several authors have explored the implications of digitalization for employment and skills. Mann and Püttmann (2021) used a patent-based measure of automation to study its employment effects, finding a positive correlation between automation technology and employment in local labor markets, specifically in the service sector. McGuinness et al. (2023) created a measure of skills-displacing technological change (SDT) and found evidence of dynamic upskilling, contradicting the common notion that technological change leads to job deskilling.

The measures and methodologies proposed in the studies discussed earlier have been leveraged to explore various aspects of the impact of digitalization on work and employment. For instance, Sorgner (2017) used the risk of job automation as a metric to investigate its relationship with occupational mobility. Sorgner's findings suggest that occupational changes, such as job loss, demotion, or starting a new job, are likely driven by high occupation-specific risks of automation. Interestingly, the study found that a shift to self-employment is more likely from jobs with a low risk of automation. This insight implies the potential for new entrepreneurial opportunities in the digital age, countering some concerns about job losses due to automation.

Further exploring the intersection between digitalization and entrepreneurship, Fossen and Sorgner (2021) studied the relationship between digitalization of occupations and entry into various types of entrepreneurship. Their research indicated that high-skilled employees and those in ICT occupations facing destructive digitalization are more likely to become entrepreneurs. However, they cautioned that entrepreneurship might not be a viable option for low-skilled individuals impacted by destructive digitalization. This finding underscores the complex interplay between digitalization, skills, and new work opportunities, and the differential impacts on different sectors of the workforce.

Fossen and Sorgner (2019) conducted a comprehensive examination of digital technologies' impact on occupations. They introduced a categorization of occupations into four broad groups, distinguishing between transformative and destructive effects of digitalization, and examining the capabilities required for each group in the digital era. Specifically, they use the computerization probabilities provided by Frey and Osborne (2017) as a measure for destructive digitalization and the degree of AI advances provided by Felten et al. (2018) as a measure for transformative digitalization.

2.2 Automation

The impact of automation on labor markets has become a salient issue in recent years. The literature on this topic covers a wide range of aspects, including the effect of automation on wage inequality, labor force participation, job satisfaction, and skill-based wage gaps, among others. A common theme in several studies is the displacement effect of automation on both high and low-skill labor, leading to wage depression initially (Acemoglu and Restrepo, 2018b), yet the net result is an increase in wage inequality.

This displacement has also led to a significant decline in labor force participation rates, particularly among workers employed in routinizable occupations (Grigoli et al., 2020). However, according to Feng and Graetz (2020), firms are more likely to automate tasks requiring more training, leading to a potential job polarization. Studies in the polarization stream like those conducted by Goos and Manning (2007) and Cortes et al. (2017) indicated a shift from middle-wage routine jobs towards both highest and lowest-wage occupations. Supporting the routinization hypothesis, Goos et al. (2021) noted that digitization decreases job opportunities for workers with routine task competencies, but increases opportunities for those with non-routine task competencies.

Recent studies have offered nuanced perspectives on the impact of automation on labor markets. While Barbieri et al. (2020) underscored the need for research on the current technological revolution's potential effects on labor markets, Downey (2021) suggested that technology only partially automates routine tasks of middle-wage occupations, enabling less-skilled workers to perform these tasks. Similarly, Dottori (2021) found that robot diffusion did not harm total employment at the local labor market level in Italy, indicating the potential for positive employment outcomes under specific conditions. Contrary to the general belief of automation leading to job loss, some studies like Domini et al. (2021) found that investments in automation-intensive goods were associated with an increase in firms' net employment growth rate. This suggests a more complex relationship between automation and employment. Supporting this view, Klenert et al. (2023) found that robot use was associated with an increase in overall employment in Europe, with no evidence of robots reducing the share of low-skilled workers, especially in the manufacturing sector.

2.3 Artificial Intelligence

The growing consensus in the academic literature suggests that artificial intelligence (AI) is having a significant and far-reaching impact on the economy, labor markets, and society at large. However, the nature of this impact and its implications for various sectors, occupations, and countries are subject to ongoing debate and research. Grace et al. (2018) set the stage by providing an estimation of AI's progression, predicting that AI would outperform humans in many activities within the next decade and in all tasks in 45 years, potentially automating all human jobs in 120 years. This potential automation of all human jobs underscores the transformative potential of AI.

When it comes to labor markets, the impact of AI is two-fold. On one hand, Acemoglu and Restrepo (2020b) note that AI is primarily used to automate existing tasks, leading to stagnant labor demand, increased inequality, and slow productivity growth. In a related vein, Tschang and Almirall (2021) stress the dual role of AI as a job displacer and a job augmenter. They show that AI tends to favor nonroutine over routine skills and higher-skilled jobs over middle-skilled ones, possibly leading to a hollowing out of middle-skilled jobs.However, on the other hand, Acemoglu et al. (2022) found that the overall impact of AI on employment and wage growth in exposed occupations and industries is currently minimal. Alekseeva et al. (2021) confirm the increasing demand for AI skills across various occupations and sectors, especially within IT, architecture and engineering, scientific, and management occupations. These job postings requiring AI skills often command a wage premium.

Echoing the potential positive impacts of AI, Damioli et al. (2023) and Yang (2022) demonstrate the job-creation potential of AI technologies and their positive association with productivity and employment. Damioli et al. showed a positive impact of AI-related patent families on employment, suggesting that AI product innovation can be labor-friendly. Yang, studying Taiwan's electronics industry, found that AI technology is positively associated with productivity and employment, while also influencing the composition of a firm's workforce towards higher education levels.

Despite these encouraging results, we should also consider the potential negative effects of AI on a global scale. Korinek and Stiglitz (2021) caution about the potential of AI and related automation technologies to reverse economic gains made by developing countries and emerging markets over the past fifty years. They suggest these technologies could increase poverty and inequality by reducing labor needs, saving resources, and creating winner-take-all dynamics that favor developed countries.

2.4 Regional differences

The rapid adoption and advancements in autonomous technologies are having broad regional and economic impacts. The papers reviewed for this analysis provide valuable insight into these implications, focusing on automation, regional growth, and income inequality. The literature on regional disparities and technological change is broad, covering various geographical areas and technological aspects. Central to this literature are the impacts of technological change on regional inequalities and labor market dynamics. Indeed, the notion of regional development has seen a profound shift in perspective in recent decades, specifically concerning its relationship with technology and innovation. An assortment of scholars has contributed significantly to the discourse, illuminating the multifaceted nature of the phenomenon.

Haseeb et al. (2019) and Li and Hao (2021) extensively explore the economic impacts of AI in Asia. Haseeb et al. demonstrate that AI has the potential to drive significant economic growth in the Asia-Pacific region, with China leading in AI research. In contrast, Li and Hao highlight that while AI improves consumer welfare inequality, it can exacerbate regional inequality of innovation in China. Building on this, Li (2023) further argues that AI technology significantly transforms household production and market production, affecting regional industrial structures differently compared to past technological advancements.

The economic and labor market impacts of AI and automation are also the subject of several US and European studies. For instance, Leigh et al. (2020) show that robotics contributed positively to US manufacturing employment. In contrast, Ge and Zhou (2020) demonstrate that different automation technologies have varying effects on gender wage gaps in US labor markets. Across the Atlantic, Zhao et al. (2020) find a positive relationship between creative workers, ICT, and regional growth in Europe. However, Blien et al. (2021) and Krenz et al. (2021) reveal that technological changes may have negative impacts on workers in routine-intensive jobs and increase income inequality. In Ireland, Rijnks et al. (2022) examine regional variations in the potential for automation adoption in the agricultural sector and its impact on employment. This study emphasizes the need to consider regional context when developing labor market policies in response to automation. Similarly, Crowley and Doran (2022) explore the potential impact of future automation and AI technologies on Irish labor markets, considering factors such as education levels, age demographics, and urban size.

Another significant strand of the literature examines the role of advanced technologies, such as AI and automation, in regional economic development. Leigh and Kraft (2018) conducted a census of the U.S. robotics industry and identified key regions, emphasizing the importance of the robotics industry for regional development. They also underscored the importance of understanding the relational and knowledge-spanning qualities of the industry to facilitate technological change. Neary et al. (2018), in their analysis of various data sources, offered insights into retailers' plans to invest in AI and Internet of Things (IoT) technologies. They also discussed the impacts of technological changes on business models and regional AI revenue, suggesting potential regional disparities in AI adoption and use.

Molle (1983) and Malecki (1983) have both provided early insights into the connection between innovation, technology, and regional development. Molle underscored the necessity of considering the spatial aspects of innovation, and the efficacy of macro innovation theory when implemented in regional contexts. This assertion is supported by Malecki, who affirmed the critical role of technology and technological change in regional development, summarizing key research in areas such as regional economic structure and corporate innovation.

Building upon a knowledge-centric viewpoint, Acs and Varga (2005) argued that disparities in entrepreneurial activity and geographical structure between countries could influence the efficiency of knowledge spillovers and overall economic growth. They noted that the agglomeration of both entrepreneurial activity and industry positively impacted technological change, even after controlling for knowledge stock and R&D expenditures. The association between social factors and regional development was highlighted by Lee et al. (2004), who proposed a strong positive correlation between social diversity, creativity, and the creation of new firms in regions. They asserted that the influx of a particular type of human capital that fosters innovation and expedites information flow could be facilitated by social diversity and human capital, leading to increased rates of new firm formation.

In conclusion, while the impact of technological change, particularly AI and automation, is generally beneficial for economic growth and development, the literature reveals an intricate relationship with regional disparities and labor market dynamics. Furthermore, literature indicates that regional development is influenced by an array of factors that extend beyond mere economic considerations. Concepts like innovation, technological change, knowledge spillovers, and social diversity are integral components that collectively shape the regional development landscape. It is, therefore, crucial that policymakers consider these aspects when designing and implementing strategies for regional development.

2.5 Hypotheses

As explored in the literature review regarding regional differences, the adoption of digital technologies is not homogeneously distributed across regions, depending largely on a variety of factors including the industrial make-up, human capital, and policy support. The question arises: how does this technological transformation interact with the pre-existing economic variety in these regions? To explore this, the hypothesis that regions with greater related variety are at higher risks of destructive digitalization but also have increased exposure to transformative digitalization is considered.

Hypothesis 1: Municipalities with greater related variety will experience both higher risks of destructive digitalization and increased exposure to transformative digitalization.

The work of Melo et al. (2009) on urban agglomeration economies suggests that the benefits of agglomeration, such as increased productivity, are not uniformly experienced. Factors like country-specific effects and industrial coverage greatly affect the results. Regions with greater related variety might experience wider elasticities when it comes to the impact of digitalization; their diverse yet interconnected industrial setup could amplify both the risks and opportunities. Muro et al. (2019) highlight that the discourse around automation and AI is complex, affecting different occupations and regions in varying manners. Their comprehensive analysis suggests that automation will bring both benefits and stresses alike. This is particularly relevant for regions with greater related variety; the diversification might expose them to a variety of automation impacts, both destructive and transformative.

Ottaviano and Pinelli (2006) focus on the role of linkages as agglomeration forces in Finnish regions. They find that firm-related demand and cost linkages are more important than worker-related cost-of-living linkages. In regions with greater related variety, these firm-related linkages could be more abundant, offering more avenues for digitalization to have transformative effects while also introducing higher complexities that could lead to destructive outcomes. Perez (2010) introduces the concept of techno-economic paradigms to understand how technological revolutions rejuvenate whole economies. For regions with greater related variety, the exposure to a new techno-economic paradigm brought by digitalization could be double-edged—highly transformative yet potentially disruptive, especially if old and new paradigms clash.

As we consider that related variety advances digitalization adoption across municipalities, we can expect that education will play a relevant mediating role in such adoption, leading to our second hypothesis relating education and digitalization adoption across municipalities.

Hypothesis 2: Municipalities with higher shares of college-educated workers will experience lower rates of destructive digitalization and higher rates of transformative digitalization.

The hypothesis posits that municipalities with higher proportions of college-educated workers will witness lower rates of destructive digitalization and higher rates of transformative digitalization. The foundational work by Griliches (1969) and further development by Krussel et al. (2000) highlight the capital-skill complementarity theory, which posits that skilled labor and capital tend to complement each other. In the era of digitalization, Eder et al. (2022) indicate that higher-skilled occupations are more likely to grow, supporting the theory's applicability.

The capital-skill complementarity theory is not just about educational attainment but also pertains to the nature of the skills and the tasks involved. High-skilled occupations, according to Krusell et al. (2000), would naturally have high complementarity with transformative digitalization. This aligns with the ‘skill-biased technological change’ assumption, as explained by Autor et al. (1998), which suggests that new technologies require more skilled labor for their operation and design.

Related to the hypothesis collecting the relation between the share of college-educated workers and digitalization, we expect that sectors composition across municipalities plays a relevant role in the adoption of digital technologies across municipalities. Concretely, we expect that municipalities specializing in services are well-poised to mitigate the risks and seize the opportunities that come with the digital age.

Hypothesis 3: Municipalities specializing in services will be less susceptible to the destructive effects of digitalization while benefiting more from transformative digitalization.

Martynovich and Lundquist (2016) provide valuable insights into how technological changes impact regional labor markets in Sweden. Specifically, they find that service industries are significant drivers in attracting workers to regions. If we extrapolate these findings, it can be suggested that regions specializing in services may find it easier to adapt to the transformative aspects of digitalization, as they already have a dynamic labor market inclined toward such sectors. Melo et al. (2009) point out the variability in the impact of urban agglomeration economies across different contexts. This heterogeneity implies that regions specializing in services could potentially leverage agglomeration benefits to buffer against the destructive aspects of digitalization.

The study by Muro et al. (2019) offers a balanced view of automation and AI, suggesting that the technology will bring both benefits and challenges. However, given that service industries often require some specific human input that is not easily automated, municipalities focusing on services might be shielded from the destructive impacts of automation to some extent. Perez (2010) elaborates on the transformative potential of technological revolutions and how they influence social and institutional changes. This implies that municipalities specializing in services, which are often quicker to adopt new technologies due to their less capital-intensive nature, could benefit more from transformative digitalization.

Ottaviano and Pinelli (2006) highlight the importance of linkages in influencing productivity and suggest that firm-related demand and cost linkages are more significant than worker-related ones. This finding could signify that service-oriented regions, which often have strong firm-related linkages due to the nature of the sector, are better positioned to gain from transformative digitalization. Wolfe (2010) discusses how resilient regions adapt to external shocks through collaborative processes. Municipalities that are service-centric often have a diverse set of stakeholders, such as government, private sector, and educational institutions, who can collaboratively build adaptive strategies against the destructive impacts of digitalization.

3 Data

3.1 Quadros de Pessoal and Portuguese Municipalities

Our regional analysis falls on the 278 Portuguese municipalities. To that end, we rely on Quadros de Pessoal (QP), a yearly longitudinal linked employer-employee dataset collected by the Portuguese Ministry of Employment and Social Security covering all private firms with at least one paid employee resulting from a mandatory survey. On the employer side, QP provides information at both the firm and the establishment level that includes location (municipality), industry/sector, number of employees and age. Given our focus on regional employment, we use the establishment-level data because it allows for greater geographical dispersion than firm-level data. On workers, QP provides information on education level, occupation, gender, age, and tenure. Unique worker, firm and establishment identifiers allow for the linking of the three units of observation. By collapsing the linked dataset we generate a regional dataset where each observation represents a yearly realization of a municipality.

Our study goes from 2010 to 2021 (the latest year made available to researchers), with a total of 3,336 observations representing a yearly average of about 2.8 million workers in 300 thousand establishments. A few examples of studies using the QP data for regional analysis include Baptista and Preto (2011), Baptista et al. (2011), Mendonça and Grimpe (2016) and, more recently, Ribeiro et al. (2022).

3.2 Dependent Variables: Regional Shares of Employment Highly Exposed to Destructive and Transformative Digitalization

To map the impacts of digital technologies on employment, Fossen and Sorgner (2019) distinguish between destructive digitalization and transformative digitalization. Destructive digitalization is deemed labor-replacing, or labor-unfriendly, and relates to computerization, meaning job automation by through of computer-controlled machinery, encompassing machine-learning technologies and robotics (Frey and Osborne, 2017). The labor-friendly side, dubbed transformative digitalization, is closely linked to artificial intelligence, a new general-purpose technology that not only requires human skills for its development but also carries strong complementarities with human labor. Fossen and Sorgner (2019) use Frey and Osborne's (2017) estimates of the computerization risks of occupations, i.e., the risk of an occupation being replaced by computerization technologies in the next two decades (destructive digitalization). For transformative digitalization, Fossen and Sorgner (2019) rely on Felten et al. (2018) measure of occupational exposure to AI advances developed between 2010–2015.

We adopt Fossen and Sorgner's (2019) strategy for the destructive side, but for the transformative side we use Felten et al. (2021) estimates of occupational exposure to forecasted developments in AI technologies. Thus, we use forward-looking measures for both the destructive and the transformative side of digitalization. Frey and Osborne (2017) and Felten et al. (2021) provide tables linking US-SOC occupation codes to risks of computerization (a probability) or exposure to AI (a score), respectively. These tables can be translated into the ISCO-08 occupation codes present in QP relying on the Bureau of Labor Statistics (2012) conversion table.

To compute the regional share of workers highly exposed to destructive digitalization, we follow Frey and Osborne (2017), Fossen and Sorgner (2019), and Crowley et al. (2021) and classify workers in occupations with 70% or higher probability of replacement by computerization as being at high risk of destructive digitalization. Similarly, we classify workers as being highly exposed to transformative digitalization if they are employed in an occupation with an AI-exposure score above zero (Fossen and Sorgner 2019). The regional shares of workers in both categories result from dividing the number of workers at high risk (or high exposure) in a municipality by the total employment level in that municipality.

3.3 Explanatory Variables

We intend to test the role of diversification agglomeration externalities and related and unrelated variety on the regional shares of employment highly exposed to destructive or transformative digitalization (Hypothesis 1). To that end, we rely on the two-digit sector-level employment entropy measures proposed by Frenken et al. (2007), and applied, among others, by Basile et al. (2017). These regional measures are based on how employment in a two-digit sector is distributed across all five-digit industries that compose it, within a region. Let S_g be a two-digit sector (with $g = 1, \dots, G$), i be all the five-digit sectors included in S_g, and p_{ri} be the share of workers in a region r that are employed in five-digit sector i. Then, the two digit employment share in region r (P_{rg}) is the sum of the five-digit shares:

$$P_{rg} = \sum_{i \in S_g} p_{ri}$$

The unrelated variety (UV) measure in region r is the entropy of the two-digit shares (between-sector-variety), given by:

$$UV_r = \sum_{g=1}^{G} P_{rg} log_2 \left(\frac{1}{P_{rg}}\right)$$

Related variety (RV) in region r is the sum of the five-digit level entropy within each two-digit sector, weighted by the two-digit shares of employment (within-sector variety):

$$RV_r = \sum_{g=1}^{G} P_{rg} \sum_{i \in S_g} \frac{p_{ri}}{P_{rg}} log_2 \left(\frac{1}{p_{ri}/P_{rg}}\right)$$

We also look into how the concentration of employment, or what Crowley et al. (2021) call the specialization of employment, influence the shares of workers exposed to digitalization. We measure the concentration of employment by a Herfindahl index of shares of employment across the two-digit sectors present in a region:

$$HI_r = \sum_{g=1}^{G} \left(P_{rg}\right)^2$$

Finally, because we argue that it is not only the diversity of employment, but also the degree of technology or knowledge intensity of employment in a region that matter to determine the share of affected workers, we compute the share of employment in high-tech and low-tech manufacturing and in knowledge-intensive and less knowledge-intensity services (Hypotheses 3). We adopt Eurostat's classification of industry-level technology and knowledge intensity based on NACE Rev. 2 industry codes.[1] Industry codes not included in Eurostat's classification are put in the catch-all category of "Other industries". The regional shares of employment in each of these categories are calculated by dividing the number of workers employed in each category in a municipality by the total employment in that municipality.

3.4 Control variables

We account for several other factors that may influence the share of workers affected by digitalization. Namely, because past technological developments have been mostly skill-biased, and have, in general, been more harmful for lower skilled and lower education workers while being complementary with skilled and educated labor (Castro-Silva and Lima, 2017), we control for the share of college educated workers in a municipality. This variable allows us to test Hypothesis 2. In this line, we also control for the average tenure of workers and the share of full time workers, which can also be thought of as measures of the skills of the region.

Some industries are dominated by male employment, and others by female employment, and technological change may be gender-biased, negatively affecting women (Aksoy et al., 2021). We thus consider that the share of female workers in a municipality may affect the region's exposure to digitalization. Technological change also has an age-biased side to it (Bartel and

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[1] See https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm. We aggregate the high-tech with medium-high-tech manufacturing categories, as well as the low-tech and medium-low-tech manufacturing categories for the sake of parsimony.

Sicherman, 1993; Bartel and Sicherman, 1998) and we analyze the mean age of workers in a municipality.

Besides the previously discussed industry variables, we also account for the share of workers employed in large firms (at least 250 employees), as firm size affects the ability of firms to innovate as well as hire and retain skilled workers (Castro-Silva and Lima, 2023). Regions with greater share of large firms may thus be more protected against nefarious effects of technology. Related to this, we include the average age of firms. Older industries and regions with older firms may be more at risk of being automated, although perhaps they can also reveal some degree of resilience. A control for total employment in municipality is included to capture effects related to the size of the municipality. Finally, we test the role population density to capture possible agglomeration effects that may occur in denser municipalities (Crowley et al., 2021).

3.5 Descriptive statistics

Table 1 presents summary statistics for our sample. The first noteworthy result is that about 54% of the Portuguese working force is at high risk of replacement by computerization (destructive digitalization). This figure is 7 percentage points above Frey and Osborne's (2017) estimates for the US population, as well as Dengler and Matthes's (2018) predictions for Germany. It is also much larger than Crowley et al.'s (2021) findings, who identify about 30% of jobs at high risk across Europe. Crowley and Doran's (2022) forecast a share of 44% of workers in Irish towns. The result for Portugal is not surprising, given that it is lagging behind the technological frontier, and with a relatively low, albeit quickly increasing, skill level, compared to the aforementioned countries. Note, however, the large disparity across some municipalities, with values ranging from 23% to 78%. With similar explanations, the share of the population at high exposure to the transformative side of digitalization stands at 34%, again with large variation across regions.

Table 1 here

The descriptive statistics also reveal a much larger degree of unrelated variety than related variety in Portuguese municipalities. This is a very different finding than that for European regions, as advanced by Crowley et al. (2021). This diference may, however, be due to methodological differences, as they compute these measures at the one-digit industry level from two-digit level employment shares, whereas we use a much more disaggregated approach. Our unit of analysis is also much more disaggregated than theirs. Regardless, our figures show that Portuguese municipalities likely do not enjoy strong Jacobs (1969) externalities originating from related variety. Instead, the degree of unrelated diversification may protect municipalities from unexpected shocks to specific industries.

Looking at the distribution of employment across the four categories of technology and knowledge intensity we see that the Portuguese economy is largely service based, with a strong share in knowledge intensive services. This may put some Portuguese municipalities at a privileged position to enjoy the transformative effects originating from AI, while being protected from replacement from computerization. As before, the municipalities are widely distinct, with a vast variation as shown by both the standard deviation and the minimum and maximum values. A similar story is found for the share of highly educated population. In conclusion, Table 1 points to very asymmetrical impacts of digitalization on employment that raise obstacles in the development of adequate policy.

4 Empirical strategy

We apply linear regression models to study variations in the share of workers exposed to destructive and transformative digitalization. Our base models are as follows:

$$Digitalization_{rt} = \alpha_r + \beta_1 RV_{rt} + \beta_2 UV_{rt} + \beta_3 HI_{rt} + Z'_{it}\gamma + D'_t\delta + \varepsilon_{rt}$$

$Digitalization_{rt}$ is either the share of employment at high risk of destructive digitalization or with a high exposure to transformative digitalization in region r in year t. RV_{rt} and UV_{rt}

represent the related and unrelated variety of a region in a given year, while HI_{rt} is the concentration of employment in that reason, as measured by the Herfindahl index. Z_{rt} is a vector containing other time-varying regressors including the share of employment in manufacturing and services, and D_{rt} a vector of year dummies (2011–2021). γ and δ are the corresponding vectors of coefficients.

The presence of time-constant regional effects that determine the dependent variables (represented by the municipality-specific intercepts, α_r) but are not otherwise captured by the set of regressors, calls for panel data estimation strategies. Ignoring these time-constant factors can yield incorrect coefficient estimates and lead to wrong conclusions. To tackle this issue, we estimate different specifications of our models through the Fixed Effects estimator, with municipality-clustered standard errors to address heteroskedasticity and serial correlation. For completeness, we also explored both OLS and Random Effects estimations (see Table 4 and Table 5 in Appendix for the OLS estimates). In both cases, the Fixed Effects estimates proved superior, and the Hausman (1978) test strongly rejects the Random Effects estimates in favor of the Fixed Effects estimator.

As argued before in Section 3.3 we consider an augmented version of our models, by explicitly controlling for the share of employment in technology/knowledge intensive industries:

$$
\begin{aligned}
Digitalization_{rt} = {} & \alpha_r + \beta_1 RV_{rt} + \beta_2 UV_{rt} + \beta_3 HI_{rt} + \beta_4 HT_{rt} + \beta_5 LT_{rt} + \beta_6 KIS_{rt} + \beta_7 LKIS_{rt} \\
& + Z'_{it}\gamma + D'_t\delta + \varepsilon_{rt}
\end{aligned}
$$

Where $HT_{rt}, LT_{rt}, KIS_{rt}, LKIS_{rt}$ are the shares of employment in high-tech manufacturing, low-tech manufacturing, knowledge-intensive and less knowledge-intensive services industries, respectively, using the “Other industries” category as the reference category (omitted).

One final note on the econometric approach is worth making. Reasonable arguments can be raised that past realizations of the dependent variables influence current values, given that several regional processes have a high degree of path dependence. If such is true, a dynamic panel data specification that includes the lagged dependent variable as a regressor is called for. We experimented with such specifications, estimating them using Generalized Method of Moments estimation approaches such as those proposed by Arellano and Bond (1991) or Blundell and Bond (1998), applying Roodman (2009) technique to reduce instrument proliferation. In general, the results were similar, although in many cases there was not always significant evidence of a dynamic behavior of the dependent variable. Thus, we opt for Fixed Effects estimates because it offers a more parsimonious approach.

5 Results and Discussion

5.1 Baseline regressions

The results from our first set of fixed-effect regressions, without accounting for technology and knowledge intensity, are displayed in Table 2. Models 1 through 3 relate to the municipal share of employment at high risk of destructive digitalization (job replacement by computerization). The dependent variable for Models 4 to 6 is the municipal employment share highly exposed to transformative digitalization (AI-complemented jobs). For each dependent variable, we first include only the variety variables and controls, then include only the employment concentration measure, and finally include all three main regressors.

Table 2 here

What first stands out in Table 2 is that, in all cases, municipalities with greater related variety will significantly have higher employment shares at high risk of destructive digitalization or high exposure to transformative digitalization. This result confirms Hypothesis 1. According to Jacobs (1969), externalities resulting from related variety can lead to greater knowledge spillovers and consequently to greater innovation and greater technology adoption. If such is the case, regions with higher related variety will be more likely to adopt digitalization technologies, both of the destructive and the transformative kind. This would expose more workers in those municipalities to said technologies, and thus increase the job-replacement and job-complementarity effects. Related variety can then favor the workers who enjoy complementarities for AI technologies, while harming those whose tasks can easily be replaced by computerization and other automation technologies. Given that technological developments are usually carried out by skilled workers, we have to bear in mind that there will be a tendency for these workers to develop and adopt technologies that favor them (i.e., transformative digitalization) possibly at the cost of increasing the share of workers at risk of the job destruction effects brought about by such technologies (often the less skilled workers) (Acemoglu 1998).

Unrelated variety also significantly promotes greater shares of employment highly exposed to transformative digitalization as well destructive digitalization (at least in Model 1). This may be due to computerization in general, and AI in particular, being general purpose technologies with a wide array of applications across industries (Agrawal, Gans, and Goldfarb 2019) and can allow for previously unlikely or impossible connections between unrelated industries. In Model 3, when accounting for variety and employment concentration, the estimate of unrelated variety remains positive but loses significance. This is likely mostly due to a lack of estimation precision given that unrelated variety and the employment concentration variables are strongly negatively correlated (Pearson correlation coefficient = -0.883, significant at 1%).

Employment sectoral concentration within municipalities does not significantly affect the proportion of workers at high risk of job replacement, though it positively influences the employment share highly exposed to AI if we also account for the variety variables.[2] Employment specialization can incentivize labor-saving innovations but also labor-augmenting developments such as some kinds of AI. However, as Crowley et al. (2021) point out, it is likely

[2] We should note, once again, the high negative correlation of the employment concentration variable with both variety variables.

that it is specialization in certain occupations rather than specialization in industries that influence exposure to automation. This argument also applies to our conclusions about relatedness: more than diversification in itself, it may be more a question of diversification into which specific industries, occupations or even functions.

Looking at the share of college-educated workers reveals that it strongly reduces the proportion of workers at high risk of replacement, while it positively increases the share of those with a high exposure to AI, confirming Hypothesis 2. These opposed effects are to be expected given that digitalization and AI in particular tend to be complementary with high skills, while also negatively affecting the unskilled.

In line with Hypothesis 3, municipalities specializing in services seem to be protected from the destructive side of digitalization, while also relishing from a greater share of workers exposed to the benefits of AI. On the other hand, larger proportions of employment in manufacturing do not significantly affect the degree to which employees are at risk of automation but favor a greater exposure to transformative digitalization. In the following section we explore these industry results further.

Our evidence also suggests that agglomeration externalities arising from population density seem to promote greater shares of workers negatively affected by job automation. Previous works have suggested that denser regions attract skilled workers and enhance innovation capabilities by matching those workers together (e.g., Duranton and Puga, 2004). If we again recall the argument that technological change tends to be endogenously determined by the skilled workers (Acemoglu 1998), denser regions will prioritize the development and adoption of technologies that increase the productivity of skilled workers (e.g., transformative digitalization) even if that might come at the cost of the least skilled.

5.2 Regressions accounting for technology and knowledge intensity

In the previous section we have risen the issue that exposure to digitalization, be it of the transformative or the destructive kind, may not exclusively be an issue of specialization, diversification or agglomeration per se, but what actually matters is into what, exactly, do municipalities specialize, into what do they diversify, and around what do they agglomerate.

In this section we attempt to shed some light into this issue by estimating our previous models but now further disaggregating our industry controls to account for technology and knowledge intensity at the industry level. Namely, we replace the shares of employment in services and manufacturing into four categories: high-technology manufacturing, low-technology manufacturing, knowledge-intensive services, and less knowledge-intensive services. By doing so, we can learn about the role of technology/knowledge intensity in shaping the exposure of municipalities to digitalization technologies, and further exploring Hypotheses 3. Table 3 presents the results of this exercise. As before, Models 7 through 9 are relative to the share of employment at high risk of destructive digitalization, while Models 10 to 12 concern the share of employment highly exposed to transformative digitalization.

Table 3 here

In line with what we found in Table 2, greater employment shares in both categories of services decrease the regional risk of destructive digitalization and increase exposure to transformative digitalization. However, the reduction in destructive digitalization is much stronger in municipalities with greater employment shares in knowledge-intensive services (KIS), whereas the exposure to transformative digitalization increases much more with the share in less knowledge-intensive services (LKIS). Our own calculations indicate that the national share of workers in KIS at high risk of destructive digitalization is below 40%, while for LKIS the share is around 57%, close to the national average (55%). For transformative digitalization, we see a

62% share of highly exposed workers in KIS and a 40% share in LKIS, again close to the national average of 42%.[3]

It is reasonable to argue that, given their higher human knowledge requirements, knowledge intensive services may be, compared to their less knowledge-intensive counterparts, strongly safeguarded from seeing broad movements towards generalized labor-saving digitalization. At the same time, the greater complexity of knowledge, combined with the greater demand for skills and expertise, makes it harder to develop (and consequently adopt) technologies that are truly labor-augmenting even despite their likely higher degree of digitalization readiness. On the other hand, regions with a larger share of less knowledge-intensive services may have a lower level of digitalization readiness. However, the exposure to transformative digitalization is still significant in these regions. This suggests that even regions with a lower level of digitalization readiness can benefit from transformative digitalization if they are able to adapt and embrace new technologies.

On the manufacturing side, we again find no significant effect on the share of destructive digitalization, for both high and low-tech industries. We do, however, find evidence of a positive and significant influence of the share of employment in low-tech on exposure to transformative digitalization, at least compared to employment in the omitted industry category, although we find no significant coefficient for high-tech. Similarly to the argument we advanced for knowledge-intensive services, the higher complexity and skill needs may hurdle the development of truly labor-augmenting technologies in high-tech manufacturing. As our national level calculations show, both manufacturing categories have much higher shares at risk of labor-replacing digitalization than the national average and services (66% in high-tech and

3 See Table 6 in Appendix.

70% in low-tech), and a smaller proportion of workers highly exposed to transformative digitalization (33% and 23% respectively).[4]

Furthermore, the inclusion of more detailed industry controls makes the effects of the variety variables on destructive digitalization insignificant (Model 9), with the related variety being especially affected. On the transformative side, the diversification variables are largely unaffected. These findings lend some credit to the questions opening this section, stating that diversification per se is insufficient to explain the degree of exposure to digitalization.

Summarizing our main results, we find that both related and unrelated variety favor greater shares of workers at high risk of replacement by technology and at high exposure to the complementary effects. In fact, in all models presented in Table 2, the coefficients of related and unrelated variety are not significantly different from each other. This suggests that it may be variety in a broader sense that increases exposure and risk, and not necessarily the two separate mechanisms of relatedness. This idea is further reinforced by the high positive correlation between the relatedness variables, revealing that municipalities with high levels of related variety will also have greater unrelated variety (Pearson correlation coefficient = 0.634, significant at 1%). The evidence presented in Table 3 also strengthen these conclusions.

It is worth developing a brief comparison to Crowley et al.'s (2021) results for European regions, given our similar focus of analysis, at least on the destructive side. While for both kinds of variety we find positive (in Model 1) or insignificant (Model 9) effects, they find no significant coefficients for related variety, but a significantly negative impact of unrelated variety on the share of workers at high risk of replacement by digitalization. Similar to us, their results for labor specialization, as measured by the Herfindhal employment concentration index,

[4] See Table 6 in Appendix.

are not significant. Finally, Crowley et al. (2021) highlight negative agglomeration effects from density on destructive digitalization, ours are positive. The differences observed may be due to different units of observation (Portuguese municipalities versus NUTS2 European regions) or because we are focusing on a single country which may be considered a laggard in terms of technologies and skills. We cannot eschew the possibility that difference are also driven by methodological differences. Crowley et al. (2021) perform a cross sectional analysis with OLS, which does not allow them to remove sources of bias that may originate from the omission of time-constant region-specific effects. Indeed, our OLS estimates in Table 4 and Table 5 in Appendix reveal a negative and significant coefficient for unrelated variety, as Crowley et al. (2021) find. Accounting for regional fixed effects plays an important role in this sort of analysis.

6 Conclusion

This paper explores the factors influencing the regional impacts of employment of both destructive and transformative digitalization, aiming to identify the aspects that policymakers may want to boost or mitigate in order to welcome the opportunities and avoid the risks of the digital wave.

Our results suggest that variety increases gaps between workers negatively affected by destructive digitalization and those benefitting from transformative digitalization. We saw that greater levels of related and unrelated variety may increase both the share of workers at risk of replacement by digitalization and the share of workers exposed to labor-augmenting technologies. This could lead to a segmentation of municipal labor markets, or even a phenomenon akin to that described in the literature as routine-biased polarization. We cannot exclude the possibility that rather than gaps within a municipality, variety can create gaps across municipalities, depending on whether a municipality's economy is dominated by an ecosystem of industries that are more exposed to one kind of digitalization. If that is true, municipalities specializing in industries that benefit greatly from the positive effects of digitalization will see employment and income rise, while regions focused on industries ripe for replacement by technology will dwindle.

These findings highlight the importance of promoting both knowledge-intensive and less knowledge-intensive services in regional development strategies. By investing in the development of knowledge-intensive services, regions can enhance their digitalization readiness and reduce the risk of destructive digitalization. At the same time, supporting the growth of less knowledge-intensive services can increase exposure to transformative digitalization and create opportunities for economic growth and innovation.

While we have attempted to advance the literature on the regional effects of technology, namely by studying the transformative side of digitalization which remains a seriously unexplored issue, as well as by using rich micro-level longitudinal data to build our sample of municipalities, it is possible that the generalizability of our results may be hampered given the focus on the Portuguese economy. Despite its limitations, our conclusions for Portugal may be applicable to several other smaller European economies even if not, hypothetically, not for larger or more skilled countries.

Despite its popularity, Frey and Osborne's (2017) methodology has been criticized in the literature, namely for considering that digitalization of tasks translates closely into the digitalization of whole occupations (e.g., Arntz et al., 2016; Arntz et al., 2017; Nedelkoska and Quintini 2018). Future work can consider complementing our analysis using, for example, Nedelkoska and Quintini (2018) estimates for probability of automation of occupations based on the OECD PIAAC Survey of Adult Skills, or Montobbio et al.'s (2023) exposure to labor-saving robotic technologies. For AI-related measures, researchers can consider alternatives to the Felten et al. (2021) classification we used, such as that proposed by Felten et al. (2018) which consider actual AI developments rather than predicted developments.

Additionally, as we argued throughout this work, relying on industry-level variety to capture knowledge spillovers may limit conclusions. In fact, even if spillovers originate from industrial relatedness, if the region in question does not have the human skills necessary to capture them and develop innovations little will come of it (Duranton and Puga, 2005). Desrochers and Leppäla (2011) propose that regional spillovers should also be measured through individual skills. Wixe and Andersson (2017) follow up on this challenge and study the impact on regional growth of education and occupation relatedness, as well as industry relatedness. Future research on the regional impacts of digitalization on employment could apply a similar approach.

Regional policymakers need to consider both the rewards and risks of greater related variety in the digital age. Policies should be dynamically tailored to the specificities of each region's related variety, industrial landscape, and human capital, as per the insights from Ottaviano and Pinelli (2006) and Perez (2010). As Muro et al. (2019) point out, the implications of automation and AI are nuanced and affect regions differently. This necessitates a careful approach in policy formulation to harness the benefits while mitigating the risks, particularly in regions with greater related variety.

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Tables

Table 1 — Descriptive statistics

	Mean	SD	Min	Max
Prop. high risk of destruct. digitaliz.	0.54	0.07	0.23	0.78
Prop. high exposure to transf. digitaliz.	0.34	0.07	0.00	0.63
Related variety (RV)	1.44	0.48	0.25	2.44
Unrelated variety (UV)	4.28	0.47	2.45	5.33
Employment concentration (HI)	0.09	0.04	0.04	0.43
Prop. in high-tech	0.03	0.05	0.00	0.39
Prop. in low-tech	0.06	0.07	0.00	0.54
Prop. in KIS	0.23	0.10	0.04	0.64
Prop. in LKIS	0.35	0.12	0.03	0.83
Prop. college	0.14	0.05	0.00	0.40
Prop. female	0.46	0.07	0.16	0.77
Mean worker age	4.20	0.18	3.48	5.00
Prop. full time	0.88	0.04	0.67	1.00
Prop. in services	0.58	0.15	0.19	0.95
Prop. in manufacturing	0.09	0.10	0.00	0.58
Population/km2	306.37	841.55	4.40	7363.60
Mean firm age	28.57	15.72	8.01	173.98
Mean worker tenure	7.76	1.40	2.29	13.50
Prop. in large estab.	0.07	0.10	0.00	0.56
Total employment	999.88	2656.70	15.00	42763
Total establishments	402.92	831.75	8.00	11439
Observations	3336			

Table 2 — Fixed-effects estimates of employment share at high risk/exposure to digitalization

	(1) Destr.	(2) Destr.	(3) Destr.	(4) Transf.	(5) Transf.	(6) Transf.
Related variety (RV)	0.022*		0.022*	0.038***		0.037***
	(0.013)		(0.013)	(0.012)		(0.012)
Unrelated variety (UV)	0.028**		0.023	0.016*		0.041**
	(0.013)		(0.026)	(0.008)		(0.016)
Employment concentration (HI)		-0.172	-0.044		-0.030	0.202*
		(0.105)	(0.219)		(0.063)	(0.107)
Prop. college	-0.295***	-0.292***	-0.295***	0.583***	0.585***	0.581***
	(0.036)	(0.036)	(0.036)	(0.041)	(0.042)	(0.041)
Prop. female	0.005	0.004	0.005	-0.007	-0.009	-0.007
	(0.031)	(0.031)	(0.031)	(0.028)	(0.028)	(0.028)
Prop. full time	0.279***	0.279***	0.279***	-0.205***	-0.208***	-0.207***
	(0.042)	(0.042)	(0.042)	(0.041)	(0.043)	(0.041)
Prop. in services	-0.262***	-0.261***	-0.262***	0.115***	0.118***	0.116***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Prop. in manufacturing	-0.008	-0.008	-0.008	0.088**	0.091**	0.090**
	(0.050)	(0.049)	(0.050)	(0.039)	(0.039)	(0.038)
Prop. in large estab.	-0.018	-0.043	-0.019	-0.059**	-0.097***	-0.055**
	(0.034)	(0.036)	(0.034)	(0.024)	(0.027)	(0.024)
log(pop. density)	0.105***	0.110***	0.105***	-0.052	-0.044	-0.052
	(0.039)	(0.039)	(0.039)	(0.035)	(0.036)	(0.034)
log(mean firm age)	-0.015	-0.016*	-0.015	-0.032***	-0.034***	-0.031***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
log(mean worker age)	-0.188***	-0.186***	-0.187***	-0.129***	-0.130***	-0.133***
	(0.049)	(0.049)	(0.050)	(0.041)	(0.041)	(0.041)
log(mean worker tenure)	-0.021	-0.019	-0.021	0.050***	0.054***	0.051***
	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
log(total employment)	0.003	0.002	0.004	-0.021**	-0.025***	-0.022***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.008)
Constant	0.192	0.346*	0.216	0.804***	0.920***	0.692***
	(0.198)	(0.196)	(0.235)	(0.192)	(0.192)	(0.205)
Observations	3336	3336	3336	3336	3336	3336
R2 within	0.210	0.208	0.210	0.299	0.293	0.300
Hausman test p-value	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors (clustered at the municipality level) in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 — Fixed-effects estimates of employment share at high risk/exposure to digitalization, with technology/knowledge intensity

	(7)	(8)	(9)	(10)	(11)	(12)
	Destr.	Destr.	Destr.	Transf.	Transf.	Transf.
Related variety (RV)		0.015	0.015		0.035^{***}	0.034^{***}
		(0.014)	(0.014)		(0.012)	(0.012)
Unrelated variety (UV)		0.025^{*}	0.025		0.015^{*}	0.042^{***}
		(0.013)	(0.025)		(0.009)	(0.016)
Employment concentration (HI)			0.002			0.217^{**}
			(0.206)			(0.108)
Prop. in high-tech.	-0.084	-0.099	-0.099	0.033	0.037	0.035
	(0.084)	(0.086)	(0.086)	(0.045)	(0.045)	(0.045)
Prop. in low-tech.	0.049	0.037	0.037	0.125^{***}	0.116^{**}	0.119^{***}
	(0.054)	(0.055)	(0.054)	(0.045)	(0.045)	(0.045)
Prop. in KIS	-0.357^{***}	-0.360^{***}	-0.360^{***}	0.082^{**}	0.083^{**}	0.084^{**}
	(0.041)	(0.041)	(0.041)	(0.041)	(0.040)	(0.040)
Prop. in LKIS	-0.183^{***}	-0.194^{***}	-0.194^{***}	0.145^{***}	0.137^{***}	0.140^{***}
	(0.032)	(0.032)	(0.032)	(0.028)	(0.028)	(0.028)
Prop. college	-0.238^{***}	-0.242^{***}	-0.242^{***}	0.604^{***}	0.599^{***}	0.597^{***}
	(0.037)	(0.036)	(0.036)	(0.040)	(0.039)	(0.039)
Prop. female	0.024	0.025	0.025	-0.001	-0.001	0.000
	(0.034)	(0.033)	(0.033)	(0.030)	(0.029)	(0.029)
Prop. full time	0.308^{***}	0.309^{***}	0.309^{***}	-0.196^{***}	-0.195^{***}	-0.196^{***}
	(0.043)	(0.043)	(0.043)	(0.042)	(0.041)	(0.041)
Prop. in large estab.	-0.057	-0.025	-0.025	-0.098^{***}	-0.061^{**}	-0.057^{**}
	(0.040)	(0.036)	(0.036)	(0.028)	(0.024)	(0.024)
log(pop. density)	0.107^{***}	0.097^{**}	0.097^{**}	-0.047	-0.055	-0.056
	(0.039)	(0.038)	(0.038)	(0.036)	(0.035)	(0.035)
log(mean firm age)	-0.006	-0.006	-0.006	-0.030^{***}	-0.029^{***}	-0.028^{***}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
log(mean worker age)	-0.172^{***}	-0.175^{***}	-0.175^{***}	-0.126^{***}	-0.126^{***}	-0.130^{***}
	(0.050)	(0.049)	(0.050)	(0.041)	(0.041)	(0.041)
log(mean worker tenure)	-0.015	-0.017	-0.017	0.055^{***}	0.051^{***}	0.052^{***}
	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
log(total employment)	-0.001	0.003	0.002	-0.025^{***}	-0.021^{**}	-0.022^{***}
	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.008)
Constant	0.253	0.157	0.156	0.892^{***}	0.794^{***}	0.673^{***}
	(0.194)	(0.197)	(0.232)	(0.186)	(0.188)	(0.199)
Observations	3336	3336	3336	3336	3336	3336
R2 within	0.222	0.225	0.225	0.296	0.301	0.303
Hausman test p-value	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors (clustered at the municipality level) in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table 4 — OLS estimates of employment share at high risk/exposure to digitalization

	(1) Destr.	(2) Destr.	(3) Destr.	(4) Transf.	(5) Transf.	(6) Transf.
Related variety (RV)	0.050***		0.050***	0.027***		0.027***
	(0.011)		(0.010)	(0.007)		(0.007)
Unrelated variety (UV)	0.007		-0.038*	0.021***		0.034***
	(0.010)		(0.020)	(0.006)		(0.012)
Employment concentration (HI)		-0.153	-0.418**		-0.154**	0.122
		(0.105)	(0.199)		(0.066)	(0.108)
Prop. college	-0.298***	-0.313***	-0.293***	0.704***	0.704***	0.703***
	(0.042)	(0.043)	(0.041)	(0.041)	(0.039)	(0.041)
Prop. female	0.070*	0.083**	0.067	-0.024	-0.025	-0.023
	(0.041)	(0.040)	(0.041)	(0.025)	(0.027)	(0.025)
Prop. full time	0.277***	0.207***	0.264***	-0.236***	-0.292***	-0.232***
	(0.060)	(0.060)	(0.058)	(0.049)	(0.052)	(0.049)
Prop. in services	-0.212***	-0.189***	-0.217***	0.120***	0.140***	0.122***
	(0.024)	(0.024)	(0.024)	(0.017)	(0.016)	(0.017)
Prop. in manufacturing	-0.011	-0.002	-0.008	0.012	0.029	0.011
	(0.034)	(0.033)	(0.033)	(0.018)	(0.018)	(0.018)
Prop. in large estab.	0.046	-0.019	0.039	-0.045*	-0.092***	-0.043*
	(0.047)	(0.039)	(0.044)	(0.023)	(0.024)	(0.023)
log(pop. density)	0.003	0.000	0.002	0.009***	0.007***	0.009***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
log(mean firm age)	-0.002	-0.002	-0.003	-0.005	-0.007	-0.005
	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)
log(mean worker age)	-0.267***	-0.255***	-0.271***	-0.090*	-0.094*	-0.090*
	(0.074)	(0.075)	(0.073)	(0.049)	(0.050)	(0.049)
log(mean worker tenure)	-0.046***	-0.055***	-0.047***	0.054***	0.054***	0.054***
	(0.017)	(0.017)	(0.018)	(0.010)	(0.010)	(0.010)
log(total employment)	-0.006	0.012***	0.000	-0.008**	0.006**	-0.009**
	(0.006)	(0.003)	(0.005)	(0.003)	(0.002)	(0.004)
Constant	0.808***	0.875***	1.027***	0.337***	0.461***	0.273***
	(0.124)	(0.116)	(0.155)	(0.082)	(0.079)	(0.096)
Observations	3336	3336	3336	3336	3336	3336

Standard errors (clustered at the municipality level) in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 — OLS estimates of employment share at high risk/exposure to digitalization, with technology/knowledge intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	Destr.	Destr.	Destr.	Transf.	Transf.	Transf.
Related variety (RV)		0.042***	0.044***		0.026***	0.026***
		(0.012)	(0.011)		(0.008)	(0.008)
Unrelated variety (UV)		0.002	-0.040*		0.023***	0.038***
		(0.010)	(0.021)		(0.006)	(0.012)
Employment concentration (HI)			-0.394*			0.138
			(0.203)			(0.106)
Prop. in high-tech.	0.108*	0.110*	0.126**	0.004	-0.041	-0.046
	(0.058)	(0.058)	(0.058)	(0.034)	(0.034)	(0.034)
Prop. in low-tech.	-0.056	-0.075*	-0.076**	0.062***	0.034	0.035
	(0.039)	(0.040)	(0.038)	(0.022)	(0.021)	(0.021)
Prop. in KIS	-0.300***	-0.289***	-0.284***	0.125***	0.119***	0.118***
	(0.040)	(0.039)	(0.038)	(0.026)	(0.027)	(0.027)
Prop. in LKIS	-0.121***	-0.166***	-0.176***	0.168***	0.119***	0.122***
	(0.026)	(0.026)	(0.025)	(0.020)	(0.020)	(0.020)
Prop. college	-0.200***	-0.222***	-0.224***	0.732***	0.699***	0.700***
	(0.052)	(0.048)	(0.047)	(0.040)	(0.041)	(0.042)
Prop. female	0.104**	0.086**	0.079*	-0.023	-0.019	-0.016
	(0.041)	(0.040)	(0.041)	(0.029)	(0.026)	(0.026)
Prop. full time	0.229***	0.287***	0.273***	-0.305***	-0.237***	-0.232***
	(0.060)	(0.060)	(0.059)	(0.052)	(0.049)	(0.049)
Prop. in large estab.	-0.046	0.010	0.002	-0.096***	-0.033	-0.030
	(0.038)	(0.046)	(0.043)	(0.027)	(0.024)	(0.025)
log(pop. density)	0.001	0.003	0.003	0.006***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
log(mean firm age)	0.000	-0.000	-0.002	-0.008	-0.006	-0.005
	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)
log(mean worker age)	-0.225***	-0.235***	-0.239***	-0.105**	-0.095*	-0.094*
	(0.073)	(0.074)	(0.073)	(0.049)	(0.050)	(0.049)
log(mean worker tenure)	-0.042**	-0.041**	-0.042**	0.063***	0.054***	0.054***
	(0.016)	(0.018)	(0.018)	(0.010)	(0.010)	(0.010)
log(total employment)	0.010***	-0.005	0.001	0.006***	-0.008**	-0.010***
	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)	(0.004)
Constant	0.762***	0.749***	0.962***	0.446***	0.339***	0.264***
	(0.113)	(0.123)	(0.157)	(0.079)	(0.082)	(0.094)
Observations	3336	3336	3336	3336	3336	3336

Standard errors (clustered at the municipality level) in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 — National level shares of risk/exposure to digitalization, by technology/knowledge intensity of industry

	Mean share destructive	Mean share transformative
High-tech manufacturing	0.660	0.330
Low-tech manufacturing	0.698	0.232
Knowledge-intensive services	0.399	0.621
Less knowledge-intensive services	0.570	0.404
Other industries	0.587	0.269
National total	0.549	0.418