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Exposure of the Portuguese Workforce to Computerization and Artificial Intelligence: A regional analysis

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Abstract

This dissertation investigates the influence of agglomeration externalities from industrial and occupational variety, as well as educational specialization, on regional workforce exposure to labor-saving and labor-augmenting digital technologies. Utilizing panel data covering Portuguese municipalities from 2011 to 2021, we employ occupational-level exposure measures developed by Frey and Osborne (2017) and Felten et al. (2021) to assess the likelihood of labor replacement by computerization and exposure to the transformative effects of Artificial Intelligence (AI), respectively.

Using a dynamic model, we find that both related and unrelated industrial variety significantly increase the share of workers at high risk of job replacement by technology, as well as those with high exposure to the complementary effects of AI. However, related occupational variety does not significantly impact the share of workers at high risk of job replacement, while unrelated occupational variety demonstrates a positive, but marginally significant, effect. Both measures of occupational variety lead to an increase in regional exposure to the job-complementing effects of AI. Additionally, our results suggest that regions characterized by a higher specialization of education are more susceptible to the adverse effects of digital technologies.

These findings highlight the importance of considering not only a region's industrial makeup but also its occupational and educational composition when assessing workforce exposure to new technologies. Our research offers valuable insights for policymakers, particularly in smaller economies, indicating the necessity of tailoring policies to regional characteristics. By doing so, policymakers can effectively mitigate risks associated with emerging technologies while maximizing their potential benefits.

Keywords: computerization; artificial intelligence; regional employment; industrial variety; occupational variety; educational specialization.

Contents

Chapter 1. Introduction

1.1 Problem Contextualization

New automation technologies are emerging at a fast pace. Their consequences on society, and, in particular, on labor markets, have been a focus of intense research for academics and economists (Kogan et al., 2023; Montobbio et al., 2022). The need to understand the effects of technology on employment has been intensified since the conclusions presented by Frey and Osborne (2017), stating that 47% of total US employment would be at high risk of automation.

Within the latest wave of technological revolution, artificial intelligence (AI) and robotics have seen the most significant technological advances (Acemoglu and Restrepo, 2018; Ing and Grossman, 2023). However, the global perspective on whether these technological developments are beneficial or detrimental to society is far from uniform, with public opinion varying significantly across the globe (Courtney and Tyson, 2020). The concerns of the population regarding technological development are causing an increase in the body of research on the potential impacts of this new wave of automation on human labor, in particular in the future availability and nature of work (Acemoglu and Restrepo, 2020b; Ing and Grossman, 2023; Montobbio et al., 2023; Muro et al., 2019).

Some authors have a pessimistic view on the topic, finding that technological advances will put several jobs at risk of being replaced (Frey and Osborne, 2017; Bowles, 2014). Others conclude that automation might not result in widespread job loss (Arntz et al., 2016; Nedelkoska and Quintini, 2018). The literature researching how automation technologies affect employment is complex and often inconsistent, given that the impact of automation is evaluated at different levels of analysis, including tasks, occupations, industries, and firms (Filippi et al., 2023).

Technologies are seen as having dual effects on labor markets, leading researchers to categorize the effects of digitalization into two types: destructive and transformative (Fossen and Sorgner, 2019). On the destructive side, technologies have displacement effects, replacing workers by automating tasks and thus contributing negatively to the labor market (Acemoglu and Restrepo, 2019). These technologies are usually linked to robotization and computerization (Kogan et al., 2023; Montobbio et al., 2024). The transformative side of digitalization involves technologies that facilitate the creation of new tasks and activities, generating new job opportunities and contributing positively to the labor market (Acemoglu and Restrepo, 2019). These technologies are typically related to AI (Fossen and Sorgner, 2019).

Several studies show that robotization and computerization can reduce overall employment and wages (Carbonero et al., 2018; Acemoglu and Restrepo, 2020b). These technologies tend to disproportionately negatively impact low-skilled, less educated workers, and those performing routine tasks (Graetz and Michaels, 2018; Autor et al., 2003). As a result, these workers are at a higher risk of being substituted and replaced in their current jobs (Arntz et al., 2016). In contrast, research on the impact of AI indicates that firms investing in AI experience an increase in employment and wage growth (Damioli et al., 2023; Babina et al., 2024). However, these positive employment effects are more pronounced for individuals with higher skills, wages, and formal education, who are also less susceptible to the adverse effects of destructive digitalization (Fossen and Sorgner, 2022; Tschang and Almirall, 2021).

Within the multilevel analysis, diverse findings in the literature show that different firms, industries, regions, and countries respond differently to new automation technologies (De Propris and Bellandi, 2021; Montobbio et al., 2022; Muro et al., 2019). Consequently, there is a pressing need to understand the implications of this latest wave of automation for the development of policies that can be fine-tuned to the distinctive economic circumstances prevailing in various regions. Simultaneously, businesses must adapt strategically to maintain their competitiveness and safeguard the well-being of their employees according to these transformative changes (Ciffolilli and Muscio, 2018; De Propris and Bellandi, 2021; Webb, 2020).

Muro et al. (2019) and Leigh et al. (2020) highlighted the importance of regional studies to understand how certain characteristics of a region can make it more or less exposed to new technologies. Pioneering work in this area was carried out by Crowley et al. (2021), who researched the influence of knowledge spillovers that may arise from related and unrelated industrial variety, on the vulnerability of European regional labor markets to job automation. However, despite the growing interest, the literature examining the regional risk of future automation is still limited (Muro et al., 2019; Frank et al., 2018).

Furthermore, in regional studies exploring agglomeration externalities, there is a predominant focus on investigating how variety among industries facilitates knowledge spillovers, thereby stimulating regional economic growth and innovation (Mascarini et al., 2023). However, there exists a gap in understanding the potential contribution of other measures of variety, particularly at the individual level, to the process of knowledge spillovers (Desrochers and Leppälä, 2011; Wixe and Andersson, 2017).

This dissertation aims to address these gaps, by investigating how regional characteristics can ease the integration and adoption of new digitalization technologies, with a specific focus on Portuguese municipalities. In particular, we look at how regional industrial, occupational, and educational specialization and diversification affects the share of workers exposed to the labor destructive and labor transformative sides of digitalization technologies. This research is essential given the urgency of this topic and the current lack of comprehensive studies regarding regional exposure to technology, and the role that variety in industries and occupations may have on this matter.

To conduct the proposed analysis, we will utilize occupational-level measures derived from the work of Frey and Osborne (2017) to assess the likelihood of labor replacement due to automation, alongside the probability of exposure to labor-augmenting AI proposed by Felten et al. (2021). We will investigate the impact of various agglomeration externalities at both the industrial and individual levels, including unrelated and related industrial and occupational variety, as well as educational specialization.

This dissertation research is relevant to help Portuguese institutions and policymakers, as well as those in countries with similar economic characteristics, in developing efficient strategies to foster the integration and adoption of a range of technologies with favorable impacts. The aim is to minimize the potential adverse effects associated with the latest wave of automation, while maximizing the beneficial outcomes it presents for employment dynamics.

1.2 Dissertation Structure

The remainder of this dissertation is organized as follows. In Chapter 2 we review the literature on this topic, in particular regarding labor-saving and labor-augmenting technologies, regional studies, and agglomeration externalities. This chapter also presents the hypotheses that will be tested. Chapter 3 describes the data sources, selected variables, and descriptive statistics. Chapter 4 explains the empirical approach employed in the study, providing an overview of the econometric model utilized. Chapter 5 presents the results obtained, along with a discussion of their implications. Finally, Chapter 6 presents the conclusions of the work, including limitations encountered and recommendations for future research. The References and Appendix are placed at the end of the dissertation.

Chapter 2. Literature Review

This chapter aims to explore the growing body of literature on digital technologies and their impact on employment at a regional level. Additionally, it seeks to examine the role of agglomeration externalities, specifically Jacobs externalities, and how they can be linked to a region's exposure to new technologies. Firstly, in Section 2.1, we explore the latest wave of technological revolution and its dual impact on labor dynamics. In Section 2.2, we present regional studies exploring how these digital technologies affect labor dynamics. Then, in Section 2.3, we introduce the concept of agglomeration externalities and explore how studies employ these measures to understand their impact on regional innovation. In this final section, we also develop the hypotheses that will be tested in this dissertation.

2.1 Labor-saving and Labor-augmenting Technologies

The dual effect of automation technologies is explained by Acemoglu and Restrepo (2019). They define the displacement effect and two opposing forces: the productivity effect and the creation of new tasks. The displacement effect is defined as a decrease in the demand for labor, wages, and employment, that results from automation that replaces workers in previously performed tasks. Conversely, the productivity effect that comes with the ability of automation technologies to perform automated tasks, can result in the reduction of production costs. This, in turn, may lead to a decrease in product prices. Consequently, lower prices could stimulate greater demand and increase production quantities. As such, firms may opt to hire more people to perform non-automated tasks, further contributing to the workforce (Barbieri et al., 2020). Another counterbalancing force is known as the reinstatement effect, which happens when technologies lead to the emergence of new jobs, tasks, and activities. They reinstate labor into a wider array of tasks, altering the task composition of production in favor of human labor. Consequently, it generates employment opportunities. Therefore, while certain technologies solely facilitate the creation of new tasks, yielding positive effects, the net impact of automation on labor depends on how these effects weigh each other (Acemoglu and Restrepo, 2019; Autor et al., 2022).

The ambiguous effects of technology in the labor market led authors to distinguish between labor-saving technologies, which can potentially replace workers and contribute negatively to the labor market, and labor-augmenting technologies, which benefit workers and positively contribute to the labor market (Autor et al., 2022; Kogan et al., 2023; Montobbio et al., 2023). Similarly, Fossen and Sorgner (2019) distinguishes between two families of effects that arise from digitalization. The first, which they call destructive effects, leads to the substitution of human labor. The second family is that of the transformative effects, where digital technologies complement human labor.

Automation and AI are transforming the occupational landscape, but they are likely to have heterogeneous effects in the labor markets (Ing and Grossman, 2023). Different results of these technologies' impacts arise according to the level of analysis that is considered (i.e., firm, sector, occupation, individual, country) (Filippi et al., 2023), and according to the tasks performed by workers, their skill set, and their level of education (Montobbio et al., 2022; Kogan et al., 2023).

Studies on automation technologies, particularly industrial robots, have highlighted their potential to reduce overall employment (Carbonero et al., 2018; Acemoglu and Restrepo, 2020b). However, research focusing on worker characteristics reveals a more complex effect. Robots have been found to disproportionately displace low-skilled and blue-collar workers, common in manufacturing sectors (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020b; De Vries et al., 2020). Manufacturing industry, often characterized by routine tasks, sees these effects amplified due to the ease with which machines can replace such labor, which is typically performed by less skilled and educated workers (Marcolin et al., 2016; Jaimovich and Siu, 2012). Other studies show that computerization can substitute workers performing routine manual and cognitive tasks and complement workers in nonroutine cognitive tasks (Autor et al., 2003).

The impact on wages reflects these employment trends, with lower-educated and manufacturing workers experiencing more significant negative effects (Acemoglu and Restrepo, 2020b; Humlum, 2021). In this line, several studies show that skilled workers are likely to benefit more, in terms of both employment and wages, relative to less skilled individuals, which are at a higher risk of being substituted by automation (Arntz et al., 2016; Barth et al., 2020; Stemmler, 2019).

The prevailing literature points to automation technologies such as robotization (robot-based automation) and computerization (computer-based automation) as having a more substantial labor-saving influence rather than a labor-augmenting one, being linked to the destructive side of digitalization (Kogan et al., 2023; Montobbio et al., 2024). However, some argue that automation can enhance competencies for nonroutine tasks (Montobbio et al., 2022), and that new jobs created in service industries can offset the losses posed by automation (Dauth et al., 2021). These diverse findings add complexity to the understanding of automation's impact on labor markets.

Research on the impact of AI on the labor market is becoming more common in the literature, since AI is thought to be among the most promising technologies being used and developed in modern times (Acemoglu and Restrepo, 2020a). Findings across studies are varied, with outcomes often dependent on the methodologies used to measure AI technologies (Autor et al., 2022). Studies examining the effect of AI technologies on labor markets reveal a dual nature, as it can act both as a job displacer, affecting middle-skilled occupations, and as a job augmenter, prioritizing nonroutine skills and higher-skilled jobs over routine jobs (Tschang and Almirall, 2021).

Several authors highlight the positive impact of AI on employment, finding that AI-patenting firms have experienced a significant increase in employment (Damioli et al., 2023), and firms investing in AI have observed notable growth in sales and employment (Babina et al., 2024). Additionally, these technologies can enhance job prospects by creating new employment opportunities and potentially leading to higher wages (Agrawal et al., 2023). Fossen and Sorgner (2022) conclude that AI contributes to wage growth and job stability, particularly benefiting those with higher formal education.

The collective research on AI underscores the constructive role that AI technologies play in enhancing different aspects of the labor market, and, thus, they can be linked to the transformative side of digitalization (Fossen and Sorgner, 2019). However, contrasting the main labor-friendly side of AI, some authors have argued that AI has been biased towards automation (Acemoglu and Restrepo, 2020a) and that AI advances may be labor-saving and resource-saving (Korinek and Stiglitz, 2021). These contrasting results show, again, the complexity of this topic.

The literature similarly shows that workers' exposure to AI varies according to the skill level and the nature of tasks performed. Different methodologies capture AI exposure without necessarily implying direct replacement or complementarity effects. Findings indicate higher AI exposure among high-skilled and highly educated workers (Webb, 2020), as well as in higher-income roles (Eloundou et al., 2023). Moreover, AI exposure tends to be more pronounced in white-collar occupations and industries (Felten et al., 2021).

The overall findings in the literature confirm that while digital technologies with destructive effects can readily replace low-skilled and less educated workers, those with higher skills and incomes are less affected and can even benefit more from the transformative effects of AI. This aligns with Acemoglu's (1998) concept of directed technological change, wherein advancements in technology tend to be endogenously determined by skilled workers, leading to a bias towards replacing low-skilled labor while complementing high-skilled one.

2.2 Regional Studies and Digitalization

If digital technologies affect workers in varied ways, their impact on regions may also differ. Several authors emphasize the urgent need to understand regional reactions to new technologies since this exposure can be different given their background and history (e.g., Muro et al., 2019; De Propris and Bellandi, 2021; Crowley et al., 2021). This understanding is critical for policymakers to facilitate smoother transitions and mitigate local impacts that can arise from new technologies (Muro et al., 2019; Ciffolilli and Muscio, 2018; Leigh and Kraft, 2018).

Balland et al. (2015) explore the concept of ”technological regional resilience”, meaning how a region's long-term ability to produce new technological knowledge is influenced by adverse technological shocks. According to their research, US cities with diverse knowledge bases that are highly related to technologies that are not yet in use in the city are better equipped to prevent technological crises and recover from them. Boschma et al. (2015) and Rigby (2012) also demonstrate how pre-existing resources and competencies in US cities can be used in novel ways to create new possibilities for regional growth.

The literature on regional-level impacts of digitalization on employment yields diverse findings. Leigh et al. (2020) report a positive contribution of robots to manufacturing employment in US metropolitan areas. Similarly, Guarascio et al. (2023) find that exposure to artificial intelligence has a favorable impact on regional employment in European regions. However, Dottori (2021) presents contrasting results in the Italian context, finding no adverse effects of robot introduction on total employment at the local labor market level. Also considering a local labor market approach, Chiacchio et al. (2018) identify a negative impact of robots on employment rates, particularly affecting young workers and individuals with secondary school degrees.

Recent research by Crowley and Doran (2023) on Irish labor markets emphasizes the significance of education levels, age demographics, and sectoral differences in determining a region's vulnerability to job automation. Regions with better-educated and higher-paid earners tend to face lower automation risk, while those with higher population densities and a greater share of knowledge and creative workers adapt better to automation shocks (Crowley et al., 2021). Additionally, Muro et al. (2019) notes gender disparities in automation exposure, with men being more exposed than women.

In studying the relationship between urbanization and automation, Frank et al. (2018) find that larger cities, characterized by higher occupational and skill specialization seem to be more resilient to the adverse consequences of automation. Building on this work, Crowley et al. (2021) consider the role of industry and regional structure to understand which European regions may be more vulnerable to job automation. Their study underscores the limited understanding in the literature regarding the relationship between agglomeration externalities and job automation risk.

2.3 Agglomeration Externalities and Digitalization

Agglomeration externalities refer to the favorable spillover effects that result from the concentration of businesses, industries, or economic activities in a particular region (Frenken et al., 2007; Glaeser and Gottlieb, 2009). In particular, Jacobs externalities (Jacobs, 1969) relate to knowledge spillovers within a region, where the variety of economic activities and sectors positively contributes to the exchange of ideas and information. In this context, a region's variety can be divided between related variety, which refers to variety within sectors, and unrelated variety, which refers to variety between sectors (Frenken et al., 2007).

Numerous studies have explored the impact of related and unrelated variety on employment (e.g., Frenken et al., 2007; Bishop and Gripaios, 2010; Hartog et al., 2012), productivity (e.g., Falcıoğlu, 2011; Wixe and Andersson, 2017), economic growth (e.g., Fritsch and Kublina, 2018; Quatraro, 2010) and innovation (e.g., Mascarini et al., 2023; Castaldi et al., 2015; Miguelez and Moreno, 2018). However, only a few studies have presented findings on the impacts of these externalities on regional exposure to new technologies (Crowley et al., 2021; Frank et al., 2018).

The literature emphasizes the important role of innovation in economic growth (Fagerberg et al., 2010), highlighting how the integration and recombination of diverse knowledge may lead to new technological development and overall economic growth. Scholars suggest that knowledge spillovers in diverse industrial settings support innovation, by facilitating the exchange of knowledge and capabilities across sectors (Mascarini et al., 2023). Therefore, understanding the relationship between variety measures and regional exposure to new technologies requires insight into how variety can be related to innovation across regions.

Studies on the impact of related variety on innovation demonstrate a positive relationship between related industrial variety and enterprise innovation (Aarstad et al., 2016; Castaldi et al., 2015; Mascarini et al., 2023). Related variety is expected to foster knowledge and technology spillovers within regions, facilitating knowledge diffusion across related industries. In addition, research also highlights a positive association between unrelated variety and innovation, particularly radical innovation (Castaldi et al., 2015; Mascarini et al., 2023; Miguelez and Moreno, 2018). Scholars argue that regions with unrelated industries possessing different yet interconnected knowledge bases may promote innovation and technological breakthroughs.

Considering the correlations between related and unrelated industrial variety with innovation, municipalities with higher levels of both types of industrial variety are expected to benefit from knowledge spillovers, thereby fostering innovation and the adoption of new technologies. According to the concept of directed technological change, technological advancements tend to be driven by skilled workers (Acemoglu, 1998). This can lead to a bias towards the development and adoption of technologies that benefit those skilled workers (i.e., transformative digitalization) while potentially increasing the risk of labor displacement for less skilled and less educated workers (i.e., destructive digitalization). Consequently, regions with higher levels of innovation are likely to develop and adopt technologies that favor the highly skilled workforce responsible for these advancements. This forms the basis of our first two hypotheses:

Hypothesis 1: *Municipalities with greater related and unrelated industrial variety will experience a higher risk of destructive digitalization.*

Hypothesis 2: *Municipalities with greater related and unrelated industrial variety will experience a higher exposure to transformative digitalization.*

Relatedness in terms of industries and the knowledge spillovers that can arise from them have been extensively explored in the literature. However, Desrochers and Leppälä (2011) claim that understanding knowledge spillovers in regions requires acknowledging the importance of individual-level interactions. Similarly, Wixe and Andersson (2017) argue that knowledge spillovers between firms are significantly influenced by interactions among their employees, underscoring the importance of studying individual-level relatedness in addition to industry-relatedness. This highlights the necessity of considering other measures of relatedness, particularly occupational relatedness, to comprehend sources of knowledge spillovers that can influence a region's exposure to new technologies.

Research indicates that the movement of individuals between firms plays a crucial role in facilitating knowledge spillovers, suggesting that it is the individuals rather than the firms themselves that drive these spillovers (Power and Lundmark, 2004). Labor mobility stands out as one of the primary mechanisms for knowledge diffusion among local firms (Neffke and Henning, 2013). Moreover, many regions are functionally specialized, which means that similar industries may exhibit different occupational compositions across regions (Duranton and Puga, 2005). This shows that relatedness in terms of industries may not necessarily go hand in hand with relatedness in employee occupations. As such, relatedness in occupations may be a source of effective learning and knowledge spillovers that are not captured by relatedness in industries (Wixe and Andersson, 2017).

Innovation tends to thrive when individuals share sufficiently similar backgrounds that can facilitate communication, but that at the same time are different enough to provide access to new ideas (Neffke and Henning, 2013; Mascarini et al., 2023). As such, related and unrelated occupational variety may foster a dynamic and innovative environment within regions, by promoting knowledge spillovers and cognitive diversity. This innovative environment may lead them to adopt several technologies. This leads us to our third and fourth hypotheses:

Hypothesis 3: *Municipalities with greater related and unrelated occupational variety will experience a higher risk of destructive digitalization.*

Hypothesis 4: *Municipalities with greater related and unrelated occupational variety will experience a higher exposure to transformative digitalization.*

Going beyond variety and focusing on specialization, Boschma (2015) argue that specialized knowledge bases in regions can limit adaptability and resilience to shocks, leading to technological lock-in due to limited recombination potential. However, Crowley et al.'s (2021) research indicates that industrial specialization itself may not significantly negatively impact a region's vulnerability to automation. This suggests that alternative measures for specialization, such as skill or educational specialization, may provide a more accurate assessment of a region's technological exposure.

Regions with a higher degree of educational specialization likely exhibit greater homogeneity in skills due to similar educational backgrounds of their population (Wixe and Andersson, 2017). Consequently, this homogeneity may result in a lack of diversity within the region, potentially limiting knowledge spillovers and innovation and making the region more vulnerable to negative risks arising from technological advancements. This leads to our fifth and final hypothesis:

Hypothesis 5: *Municipalities with a higher level of educational specialization in a particular area will experience a higher risk of destructive digitalization.*

Chapter 3. Data

3.1 Quadros de Pessoal and Portuguese Municipalities

The regional analysis will cover 278 Portuguese municipalities in Continental Portugal, excluding the autonomous regions of Madeira and Azores. The latter are excluded because of their different legal and fiscal regimes. The data used in this work is from Quadros de Pessoal (QP), an annual longitudinal linked employer–employee database, that has information on private companies, establishments, and workers. The data is collected by the Portuguese Ministry of Labor and Social Solidarity through a mandatory yearly survey, and includes information on all private firms with at least one paid employee.

Regarding the employers, QP includes information about firms and their establishments, namely their geographical location (municipality), industry/sector, number of employees, firm age, and sales volume. Since our purpose is to conduct a regional study, we focus on the establishment-level data, since it allows for more geographical dispersion than firm-level data, given that one firm can have multiple establishments across the country. Concerning the employees, QP provides information about age, gender, tenure, type of contract, level of education, occupation, and wage. The three types of datasets (companies, establishments, and workers) are linked through unique identifiers of each company, establishment, and worker.

Our analysis comprises the ten-year period from 2011 to 2021 (the latest year available for researchers), resulting in a sample of 3058 observations (one for each year and municipality). The observations represent a yearly average of about 2.8 million workers across 320 thousand establishments. Other studies using QP data to conduct regional analysis include, among others, Mendonça and Grimpe (2016) and Ribeiro et al. (2022).

3.2 Dependent Variables

The literature on the new wave of automation often distinguishes technologies based on their effect on the labor market. The dual-effect documented is sometimes referred to as labor-saving and labor-augmenting technologies (Kogan et al., 2023; Montobbio et al., 2024; Acemoglu and Restrepo, 2018; Autor et al., 2022), or, alternatively, as destructive digitalization (labor-unfriendly) and transformative digitalization (labor-friendly) (Fossen and Sorgner, 2019). Although there are different results in the literature, labor-saving, or destructive digitalization, has been linked to computerization (job automation using computer-controlled equipment) and robotics (Frey and Osborne, 2017; Montobbio et al., 2024; Fossen and Sorgner, 2019), while labor-augmenting, or transformative digitalization, relates to artificial intelligence (Fossen and Sorgner, 2019; Damioli et al., 2023; Babina et al., 2024; Yang, 2022). In our work, we explore how regional characteristics determine the share of workers highly exposed to labor destructive and labor transformative digitalization.

Regarding labor-saving technologies, or computerization, Frey and Osborne (2017), offer a comprehensive table linking US-SOC occupation codes to the risks of computerization, quantified by probabilities, to understand the risk of an occupation being replaced by future computerization technologies. On labor-augmenting technologies or AI-related technologies, Felten et al. (2021) propose a measure to link advances in AI to occupational abilities, based on expected future developments in AI technologies. They provide mappings from US-SOC occupation codes to exposure levels to AI, measured by numerical scores.

In the present work, we consider these two forward-looking measures, which means that the measures employed are calculated based on expectations of future technological developments. The tables originally constructed using US-SOC occupation codes can be effectively translated to International Standard Classification of Occupations 2008 (ISCO-08) occupation codes, which are the ones present in our dataset, via official crosswalks sourced from the Bureau of Labor Statistics (2012).[1] By aligning the US-SOC codes with the corresponding ISCO-08 codes through this conversion table, the occupational exposure metrics derived from Frey and Osborne (2017) and Felten et al. (2021) can be applied to the occupations represented in the QP dataset.

To compute the regional share of workers highly exposed to destructive digitalization, using Frey and Osborne's (2017) measure, we consider that employees who have occupations with a 70% or higher probability of replacement by computerization are at a high risk of destructive digitalization, as in Frey and Osborne (2017), Fossen and Sorgner (2019), and Crowley et al. (2021). Concerning transformative digitalization, workers are classified as highly exposed to AI when they are in occupations with Felten et al.'s (2021) AI-exposure score above 0.

Following the identification of workers at high risk (or high exposure) across all measures for each municipality, we calculated the regional shares of such workers by dividing the number of high-risk workers by the total employment level of the respective region. This process allowed us to generate two distinct dependent variables, representing the regional share of employment at high risk/exposure to destructive/transformative digitalization.

3.3 Explanatory Variables

The set of independent variables used to understand which factors may influence the shares of workers exposed to digitalization are related and unrelated variety in industries and occupations and a measure of the specialization of education.

The computation of related and unrelated variety was based on the one developed by Frenken et al. (2007) measuring variety using the entropy approach. This method is used by several authors studying regional related and unrelated variety at industrial and occupational levels (e.g., Wixe and Andersson, 2017; Crowley et al., 2021; Basile et al., 2017; Tavassoli and Jienwatcharamongkhol, 2016). The entropy measure for related variety measures the within diversity (diversity within each sector), while unrelated

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[1] See https://www.bls.gov/soc/ISCO_SOC_Crosswalk_process.pdf for details

variety measures the between diversity (diversity between sectors) in, as desired for our case, industries and occupations.

The main advantage of these measures is that they can be decomposed at each sectoral digit level (Frenken et al., 2007). For the calculation of variety at the industrial level, we consider the NACE Rev. 2 industry codes.[2] Let S_g (g = 1, ... , G) be a two-digit sector, i all the five-digit sectors that belong to S_g and p_{ri} the share of workers in a certain region r that are employed in a five-digit sector i. The two-digit share of employment in two-digit sector g in region r (P_{rg}), can be obtained by summing the p_{ri} of the five-digit sectors within g:

$$P_{rg} = \sum_{i \in S_g} p_{ri} \tag{3.1}$$

Then, the unrelated variety in a region r (UV_r) is the entropy at the two-digit level, given by:

$$UV_r = \sum_{g=1}^{G} P_{rg} \log_2 \left(\frac{1}{P_{rg}} \right) \tag{3.2}$$

The related variety in a region r (RV_r) is the sum of five-digit level entropy within each two-digit sector, weighted by the two-digit shares of employment, given by:

$$RV_r = \sum_{g=1}^{G} P_{rg} \sum_{i \in S_g} \frac{p_{ri}}{P_{rg}} \log_2 \left(\frac{1}{p_{ri}/P_{rg}} \right) \tag{3.3}$$

Higher values obtained by equations (3.2) and (3.3) indicate higher levels of unrelated and related variety in a region, respectively.

As in Wixe and Andersson (2017), unrelated and related variety for the occupational dimension is calculated as above, but using the occupational codes (ISCO-08) at the two- and five-digit levels present in the dataset.

To further complement the analysis, we also compute a variable measuring the concentration of college-educated people in a particular educational field, i.e., the specialization of education. We measure this concentration by a Herfindahl index given by:

$$HI_r = \sum_{s} \left(\frac{y_{rs}}{y_r} \right)^2 \tag{3.4}$$

Where y_{rs} is the level of employment in a region r across the three-digit Portuguese Classification of Education and Training Areas codes, s.[3] y_r is the level of employment in a region r, considering only college-educated workers. A higher value of this index indicates a greater specialization of education in a particular academic field, respectively, in each region.

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[2] https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

[3] https://certifica.dgert.gov.pt/legislacao/cnaef-classificacao-nacional-de-areas-de-educacao-e-formacao-pdf.aspx

3.4 Control Variables

Considering the data available in our dataset, it is possible to control for other factors that can influence the exposure of a municipality to digitalization.

Significant literature emphasizes that people with different levels of education and skills are differently affected when it comes to technological developments. In general, less educated and less skilled people tend to be more negatively affected by digitalization than more educated and skilled people (Muro et al., 2019; Crowley and Doran, 2023; Graetz and Michaels, 2018; Arntz et al., 2016). To account for the educational level of the employees in a certain municipality, we control for the share of college-educated workers. To consider the different skill composition in a region, we control for the share of full time employees and the monthly wage.

Technological change and adaptation may have different effects depending on the gender of each employee. In fact, Aksoy et al. (2021) and Brussevich et al. (2019) argue that women may be more negatively affected than men. However, Muro et al. (2019) and Acemoglu and Restrepo (2020b) find the opposite. To take this into account in our model, we control for the share of female workers in a municipality. The automation risk can also affect differently the workers according to their age. Crowley and Doran's (2023) results show that towns with younger populations are generally less exposed to automation risk than towns with older populations. Considering this, we control for the mean age of workers in a municipality.

To account for other firm-related factors that might affect the regional exposure to automation, we also control for the regional share of workers employed in the tertiary sector of industry (services). Indeed, Henning (2020) highlights the declining significance of manufacturing across regions, alongside the emergence of a robust business services sector in metropolitan areas, and Dauth et al. (2021) find there have been new jobs created in services, in contrast with the decline in manufacturing roles. Therefore, regions where the population is mostly employed in services industries may be at a lower risk of job replacement, and may be more exposed to labor-complementing technologies.

We also control for the proportion of workers employed in firms with at least 50 employees, capturing the share of workers in medium and large firms. This factor is pertinent as larger firms are often presumed to be more inclined towards adopting new technologies, in particular, industrial robots (Acemoglu and Restrepo, 2020b) and have a greater capacity to recruit and retain skilled employees (Castro-Silva and Lima, 2023). Consequently, regions with a greater concentration of larger firms may exhibit greater resilience to the adverse impacts of technological advancements. The analysis also includes a control for population density, to account for possible agglomeration effects that may occur in denser municipalities (Crowley et al., 2021; Wixe and Andersson, 2017).

3.5 Descriptive Statistics

To have a visual representation of the relationship between the dependent variables and the main independent variables, we present several quantile maps in Figure 3.1. The quantile maps represent the distribution of the share of employment at high risk of destructive digitalization (Panel A), the share of employment at high exposure to transformative digitalization (Panel B), and the distribution of industrial (Panel C) and occupational variety (Panel D) across the 278 Portuguese municipalities considered in 2021.[4]

These quantile maps illustrate significant regional discrepancies within the country concerning workforce exposure to both destructive and transformative digitalization, as well as industrial and occupational variety. Panel A shows that the share of employment at high risk of destructive digitalization is more concentrated in the northern regions, which have a high concentration of industrial and manufacturing activities. This is expected, as these sectors are more associated with routine tasks that can be easily automated. Panel B reveals that exposure to transformative digitalization is more dispersed throughout the country, with higher exposure in more urbanized regions like Porto and Lisbon, where there are more people employed with higher levels of education and thus, employed in white-collar occupations. When comparing the maps in Panels A and B, it is evident that municipalities with larger shares of workers at higher risk of being replaced by computerization generally have lower exposure to AI-related technologies, and vice versa.

Both maps developed for the variety measures (Panels C and D) show that, although they capture different characteristics, regions with greater industrial variety also have greater occupational variety. However, differences arise, particularly in the southern municipalities. It can also be noticed that this diversity is more pronounced in the central and northern coastal regions. This may be attributed to the fact that these regions have higher population densities and more significant economic activities, which attract a variety of industries and a more diverse workforce.

The descriptive statistics for our sample are presented in Table 3.1. Regarding the exposure measures, it can be concluded that 54% of the Portuguese workforce is at high risk of destructive digitalization, which means that it is at high risk of being replaced by computerization over the next decade or two. This value is 7 percentage points above the probability estimated by Frey and Osborne (2017) for US employment, 24 percentage points above the one obtained by Crowley et al. (2021) for European regions, and 10 percentage points above the one calculated by Crowley and Doran (2023) for Irish towns. This high value of the proportion of workers at high risk of having their jobs automated when compared to other European countries can be explained by the fact that the Portuguese economy has a significant portion of jobs in sectors such as manufacturing and agriculture, which involve more routine tasks and thus can be automated more easily with advancements in technology. Portugal has also a large amount of older and thus, less educated and skilled people, which potentially makes the country less equipped to adapt to technological changes and more susceptible to automation. This exposure varies from 32% to 74%, which shows large discrepancies within the country.

The average exposure to transformative digitalization is 34%, but ranges between 15% and 63%. The heat map shows that, on average, urban municipalities are more highly exposed to AI than rural ones. This is as expected, since Felten et al. (2021) show that the occupations with higher exposure to AI consist almost entirely of white-collar occupations that require higher educational levels, which usually happens in more urbanized regions.

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[4] The total variety measures correspond to the sum of the unrelated and related variety variables.

Table 3.1: Descriptive statistics

Variables	**Mean**	**SD**	**Min**	**Max**
Prop. high risk of destructive digitalization	0.54	0.06	0.32	0.74
Prop. high exposure to transformative digitalization	0.34	0.06	0.15	0.63
Related Industrial Variety	1.44	0.47	0.25	2.44
Unrelated Industrial Variety	4.28	0.48	2.45	5.33
Related Occupational Variety	1.85	0.35	0.74	2.70
Unrelated Occupational Variety	4.54	0.20	3.01	4.86
Specialization of education	0.10	0.02	0.06	0.35
Prop. college	0.14	0.05	0.04	0.41
Prop. full time	0.88	0.03	0.67	0.97
Mean monthly salary	832.94	147.88	539.77	1924.98
Prop. female	0.47	0.06	0.17	0.65
Mean worker age	41.72	1.50	36.68	47.76
Prop. services	0.59	0.14	0.21	0.95
Prop. medium establishments	0.19	0.10	0.00	0.56
Prop. large establishments	0.07	0.10	0.00	0.52
Population/km^2	305.89	839.38	4.4	7292.4
Observations	3058			

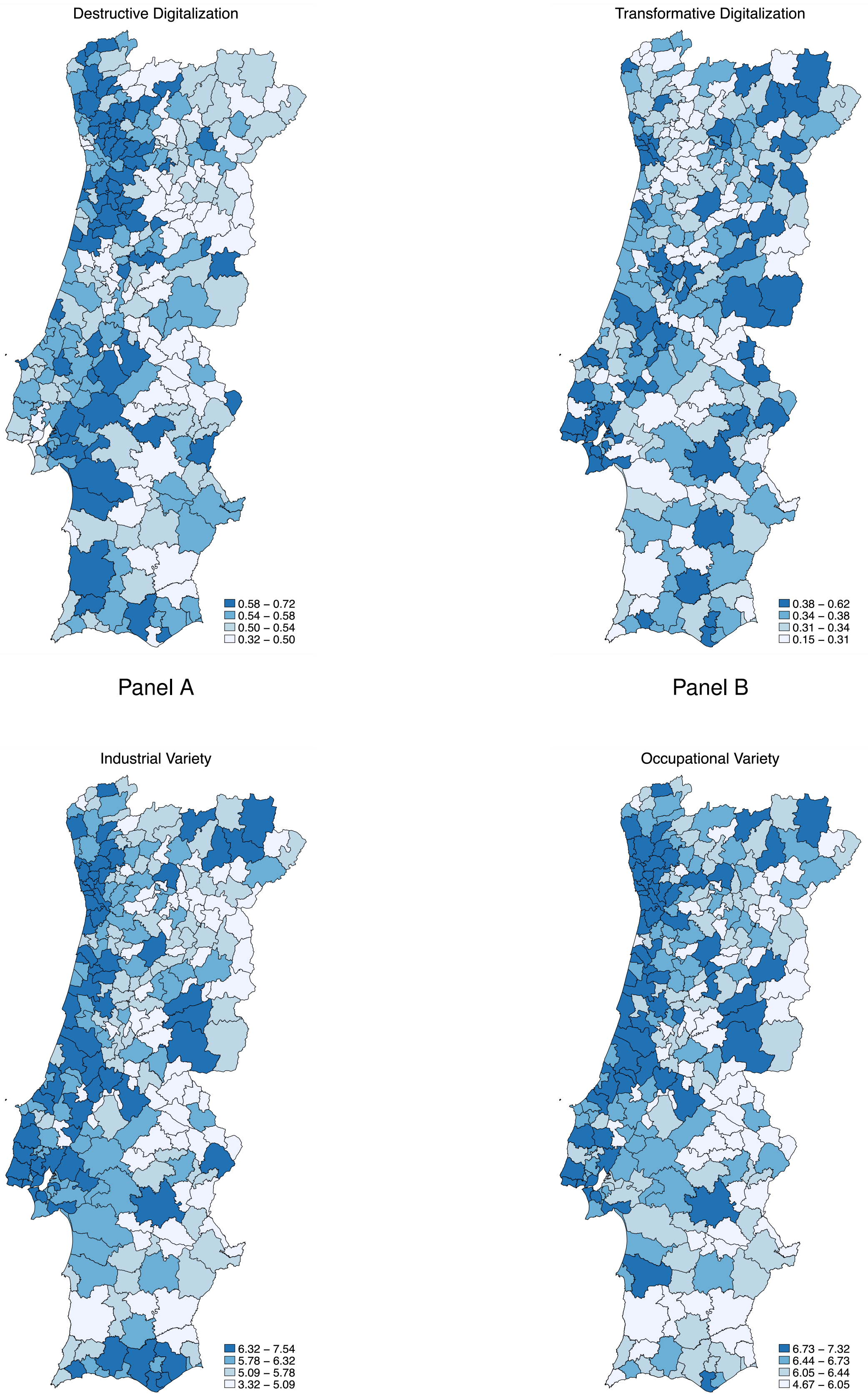
For the industrial variety measures, related variety has an average value of 1.44 which is significantly lower than the average value for unrelated variety, which averages 4.28. These values are in agreement with the ones obtained by Wixe and Andersson (2017) for Swedish regions but are very different from the ones obtained by Crowley et al. (2021) for European regions. This may be due to the fact that Wixe and Andersson (2017) also analyze regions within a country and use two-digit and five-digit industry codes to compute the industrial variety measures, whereas Crowley et al. (2021) study European regions at the more aggregated NUTS 2 level and also compute more aggregate variety measures using one-digit and two-digit industry codes. However, Wixe and Andersson's (2017) values show more similar values between unrelated and related variety when compared to the ones obtained in our work. This shows that Portuguese municipalities have much more variety between sectors when compared to the variety within sectors, possibly experiencing less knowledge spillovers within a region but can be more protected from external and unexpected shocks (Frenken et al., 2007).

The average values for occupational variety are similar to the ones obtained for industrial variety. For related occupational variety, we have an average value of 1.85, while for unrelated variety the average is 4.54. Once again, the values differ more between themselves when compared to the values of occupational variety obtained by Wixe and Andersson (2017), which means that Portuguese municipalities reveal a much higher degree of unrelated occupational variety than related occupational variety.

The average specialization of education is relatively low (0.10). This suggests that individuals in Portuguese municipalities possess diverse knowledge backgrounds, potentially resulting in regions with a heterogeneous skill set. This diversity may enhance resilience to shocks and facilitate diversification. However, it is important to note that this value varies significantly across the country, ranging from 0.06 to 0.35. Table 3.1 also reveals that the average proportion of individuals with a college education is relatively low at 0.14, indicating a potential vulnerability to displacement by computerization. However, this figure varies significantly across municipalities, ranging from 0.04 to 0.41. Conversely, Portugal demonstrates a high percentage of individuals employed in services, standing at 0.59. This suggests that Portuguese municipalities may be well positioned to benefit from the transformative impacts of AI.

Nevertheless, this variable also exhibits considerable variability across the country, ranging between 0.21 and 0.95. The proportion of individuals employed in large establishments is notably low, standing at 0.07 when compared to the average value of people employed in medium establishments (0.19). This trend suggests that the population may benefit less from the capacity that large firms typically have in adopting new technologies, which makes them more resilient against technological developments.

The wide range of minimum and maximum values, alongside the standard deviation, underscores the high diversity of the industrial composition and the workforce's educational levels, jobs, and occupations among Portuguese municipalities. This diversity shows the importance of tailoring policies, concerning the impact of digitalization on employment, to the unique characteristics of each region.



Panel A

Panel B

Panel C

Panel D

Figure 3.1: Quantile maps of mean employment at high risk of destructive digitalization, high exposure to transformative digitalization, industrial variety and occupational variety, for 2021 (darker colour implies greater risk, exposure or variety).

Chapter 4. Empirical Strategy

To analyze the association between the regional's industrial, occupational and educational structure, and the exposure of workers to destructive and transformative digitalization, we should consider that the previous exposure of a region to digitalization can influence its present exposure. This indicates that the share of employment in a region that is at high risk/exposure to destructive/transformative digitalization may have a path dependency. Therefore, our base model corresponds to a dynamic model given by the following expression:

$$Digitalization_{rt} = \beta_1 Digitalization_{r,t-1} + \beta_2 RV_{rt} + \beta_3 UV_{rt} + \beta_4 HI_{rt} + Z_{rt}\gamma + D_t\delta + \alpha_r + \varepsilon_{rt} \quad (4.1)$$

Where $Digitalization_{rt}$ is the proportion of workers in region r and in year t at high risk of destructive digitalization or with a high exposure to transformative digitalization, and $Digitalization_{r,t-1}$ represents the first lag of this variable.[1] RV_{rt} represents a row vector of related variety in industries and occupations of a region in a certain year, UV_{rt} is the corresponding vector for unrelated variety, and HI_{rt} is the Herfindahl index that measures the degree of specialization of education in a region. Z_{rt} is a vector that contains other time-varying regressors (all regional control variables mentioned in Section 3.4), and D_t is a vector of year dummies, to account for wide time-specific economic shocks. The coefficient β_1 allows us to test the path dependency of the dependent variables. Coefficients, β_2, β_3, and β_4, allow us to test the effects of the main explanatory variables of interest, and thus, test the hypotheses developed in Section 2.3. Regarding the error terms, α_r represents the time-constant, region-specific, error and ε_{rt} the idiosyncratic, or time-varying, error.

The existence of a time-constant error term, α_r, captures unobserved regional factors that can influence the dependent variables. If these factors are not considered in the estimation models, our results can be biased and, thus, lead to wrong conclusions. In such cases, it is important to use panel data models, as they allow for the unobserved time-constant factors to be correlated with the explanatory variables and still produce unbiased results (Wooldridge, 2013).

The Fixed Effects estimator is a widely used panel data estimator since it performs a transformation that removes the unobserved time-constant effects prior to estimation. Accordingly, assuming strict exogeneity of the independent variables (i.e., independent variables are not correlated with the idiosyncratic error term ε_{rt} in all moments in time), the Fixed Effects estimator is unbiased (Wooldridge, 2013). However, applying the Fixed Effects estimator to remove α_r in a dynamic model is inconsistent, because the within model will have a first regressor that is correlated with the error term through the first lag of the

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[1] For a more parsimonious approach, our base model only includes the first lag of the dependent variable, but the effects of additional lags were also tested. No significant changes were found.

dependent variable, $Digitalization_{r,t-1}$ (Cameron and Trivedi, 2022).

Instrumental variables and generalized method of moments (GMM) estimators are commonly employed in estimating linear dynamic panel data models (Breitung et al., 2022). Despite their widespread use, even the latest versions of these estimators, such as the system GMM estimator, suffer from the weak-instruments problem (Bun and Windmeijer, 2010). However, there exist efficient alternatives, particularly when it can be assumed that all regressors (except the lagged dependent variable) are strictly exogenous. Kiviet (1995) argues that the within-group, or Least-Squares Dummy Variables (LSDV) estimator, has usually a much smaller variance when compared to the variance of GMM estimators. They conclude that the best way to handle dynamic panel bias is to perform LSDV and correct the results for the bias.

Therefore, in this econometric analysis, assuming strict exogeneity of all other regressors besides the lagged dependent variable, a bias-corrected method of moments estimator developed by Breitung et al. (2022) is employed. This method allows to directly correct the dynamic panel data bias inherent to the Fixed Effects estimator, while preserving the small variance characteristic of this estimator. One advantage of the Breitung et al. (2022) estimator is that it does not depend on the choice of a preliminary consistent estimator and standard errors are readily available. It can handle both Fixed Effects and Random Effects assumptions, heteroskedastic errors, cross-sectional dependence and higher-order autoregressive models. An example of another study employing this estimator is the work developed by Nwani et al. (2023).

Breitung et al.'s (2022) approach allows for the estimation of dynamic Fixed Effects and dynamic Random Effects models, as well as hybrid versions.[2] The Fixed Effects variant aligns with the adjusted profile likelihood estimator proposed by Dhaene and Jochmans (2016), and for models featuring a single lag of the dependent variable, it corresponds to the iterative bias-corrected estimator of Bun and Carree (2005).

In this study, we employ this estimator under the assumption that all explanatory variables are strictly exogenous with respect to the idiosyncratic error component. For every regression, we perform the Arellano and Bond (1991) test for autocorrelation of the first-differenced residuals. This test intends to check if the idionsyncratic errors at order two are serially correlated. If ε_{rt} are serially uncorrelated, we will have, by definition, correlation of the first differenced errors with its first lag, but not with earlier lags. This test is performed twice, at order one, AR(1), and at order two, AR(2). For the estimates to be correct, we want to reject the null hypothesis (H$_0$: No autocorrelation of the first-differenced residuals) at order 1, but not at order 2 (Arellano and Bond, 1991). This is because the first difference of independently and identically distributed idiosyncratic errors are expected to be serially correlated (StataCorp., 2013). The estimator used also provides a heteroskedastic-consistent estimate of the variance-covariance matrix. With this estimator, the robust standard errors effectively adjust for cross-sectional dependence (Breitung et al., 2022).

Since it is possible to perform the estimation with the Fixed Effects or Random Effects model, both are performed for each regression. Therefore, for every regression, we also ran the Hausman (1978)

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[2] The Stata command that implements this estimator is *xtdpdbc*, developed by Kripfganz (2021).

test. In all cases, the test strongly rejected the Random Effects estimations in favor of the Fixed Effects estimator, so only the latter will be presented in the results. The Fixed Effects version of this estimator is a just-identified method-of-moments estimator, so the use of instruments or corresponding validations (Kripfganz and Breitung, 2022) is not necessary.[3]

For completeness, the regressions were also estimated using GMM estimation approaches.[4] Both Difference and System GMM were performed, considering again every regressor as exogenous (except the lagged dependent variable). However, according to the specifications applied (One-step/Two-step, Difference/System GMM), many different results were obtained. Indeed, Roodman (2009) argues that one of the disadvantages of these estimators is that they are complicated and can easily generate invalid estimates, even when techniques to reduce instrument proliferation are applied. As such, the results obtained for these models are still presented in Tables A.4 and A.5 in Appendix A, but we opt for the more parsimonious Fixed Effects version of the bias-corrected method of moments estimator to perform our analysis.

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[3] The code developed in *Stata* to perform the regressions can be consulted in Appendix B.

[4] The Stata command utilized for these estimations is *xtabond2*, developed by Roodman (2009).

Chapter 5. Results and Discussion

For the discussion of the results obtained from the regressions using the Fixed Effects version of the bias-corrected estimator, we will sequentially analyze three sets of regressions[1]. First, we consider the regressions that use the industry variety variables (Table 5.1), then the ones that consider occupational variety variables (Table 5.2), and finally, the ones that contain all the main explanatory variables (Table 5.3). All the results contain the variable that measures the degree of specialization of education in each region.

To follow a more parsimonious approach, the tables of results presented in this section only contain the coefficients for the two most relevant control variables, namely the share of college-educated workers and the share of workers employed in services industries. The results featuring all control variables considered can be found in Tables A.1, A.2 and A.3 in Appendix A. Aditionally, in every table of results, it is presented the p-values of the Arellano and Bond (1991) test for serial correlation at order one and at order two.[2]

For every regression performed, the lagged dependent variables (*Prop. Destructive*$_{t-1}$ and *Prop. Transformative*$_{t-1}$) show a positive and highly significant effect, which comproves the path dependency within this model. This shows that a region's high risk/exposure to destructive/transformative digitalization is influenced by its exposure in the preceding year. We also computed models incorporating second and third lags of the dependent variable, but they did not yield significant results. This lack of significance implies that a region's susceptibility to the effects of job replacement or job complementing technologies is contingent on its exposure only in the immediate prior year, which indicates the absence of a long-term effect. The coefficients of the lagged dependent variables are less than 1, which satisfies the stability condition required for a dynamic process (Kiviet, 1995).

Table 5.1 presents the regression results concerning the municipal share of employment at high risk of destructive digitalization (Models 1 and 2) and with high exposure to transformative digitalization (Models 3 and 4). For each measure of digitalization, first, we include only the industrial variety variables and controls, and, then, we include the educational specialization measure.

We can first notice that both measures of industrial variety are positive and highly significant across all four models, which confirms Hypothesis 1 and 2. This implies that municipalities with greater unrelated or related industrial variety will experience an increase in the proportion of employment highly vulnerable to destructive digitalization and highly exposed to transformative digitalization.

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[1] Models with Random Effects were also tested, but the Hausman (1978) test leads to a rejection of these in favor of Fixed Effects for every regression.

[2] AR(1) p-values indicate the presence of serial correlation at order one, while AR(2) p-values indicate the absence of serial correlation at order two for every regression.

Table 5.1: Estimates of mean employment share at high risk/exposure to digitalization, with related industrial variety, unrelated industrial variety and specialization of education

	(1) **Destr.**	**(2)** **Destr.**	**(3)** **Transf.**	**(4)** **Transf.**
Related Industrial Variety	0.023***	0.023***	0.022***	0.022***
	(0.008)	(0.008)	(0.005)	(0.005)
Unrelated Industrial Variety	0.020**	0.021**	0.018***	0.017***
	(0.008)	(0.008)	(0.005)	(0.005)
Specialization of education		0.061**		-0.037
		(0.029)		(0.037)
Prop. college	-0.153***	-0.165***	0.508***	0.515***
	(0.045)	(0.046)	(0.038)	(0.039)
Prop. in services	-0.173***	-0.174***	0.041**	0.041**
	(0.029)	(0.029)	(0.019)	(0.019)
Prop. Destructive$_{t-1}$	0.566***	0.564***		
	(0.044)	(0.044)		
Prop. Transformative$_{t-1}$			0.491***	0.490***
			(0.035)	(0.035)
Constant	1.374***	1.394***	-0.187	-0.198
	(0.264)	(0.265)	(0.199)	(0.197)
Observations	2780	2780	2780	2780
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.790	0.774	0.907	0.867
Hausman test p-value	0.000	0.000	0.000	0.000

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

Jacobs externalities measured by related variety are expected to facilitate knowledge and technology spillovers, thereby fostering innovation and the adoption of new technologies. This occurs as knowledge diffuses across various industries, enabling firms to merge and apply ideas from diverse perspectives (Jacobs, 1969; Frenken et al., 2007; Aarstad et al., 2016). Consequently, regions with greater related industrial variety are more likely to adopt digitalization technologies, whether they yield job-replacement or job-complementing effects. In this case, related variety could have adverse effects on workers with occupations susceptible to easy replacement by computerization and other forms of automation, but could also benefit the ones who enjoy the complementarities that come with AI technologies.

Regarding unrelated industrial variety, studies in the literature have demonstrated its association with innovation. Castaldi et al. (2015) reveal that unrelated variety, measured through patents, is associated with breakthrough innovations, a finding supported by Miguelez and Moreno (2018), who emphasize its role in fostering radical innovations. Mascarini et al. (2023) provide more evidence for these conclusions by demonstrating the positive impact of unrelated variety on radical innovations at the regional level. Castaldi et al. (2015) underscore that when unrelated knowledge converges to create a new invention, it paves the way for later breakthroughs in technology and radical innovations. This effect can result in the emergence of new operational principles, functionalities, and applications, prompting regions to adopt new technologies. These technologies may replace human labor, thereby explaining the positive relationship between unrelated industrial variety and the increase in the share of employment vulnerable to job destruction effects. These new technologies can also complement labor, which explains the positive effect that this variable has on regional exposure to transformative digitalization.

Given the association between both related and unrelated industrial variety with innovation and radical innovation (respectively), which drives the adoption of new technologies by individuals, it is reasonable to argue that these measures contribute to an increase in the proportion of workers highly exposed to both destructive and transformative digitalization. This means that they increase the proportion of individuals at high risk of being replaced by computerization, who are often less skilled, less educated, and employed in routine-based jobs. Simultaneously, they also lead to a higher proportion of individuals exposed to transformative digitalization, often characterized by having higher skill and educational levels, and being employed in non-routine jobs (Goos et al., 2021; Violante, 2008). The outcome aligns with the concept of directed technological change, which suggests that skilled workers primarily drive technological advancements (Acemoglu, 1998). This tendency leads to a bias towards the development and adoption of technologies that benefit those skilled workers (transformative digitalization), potentially increasing the risk of job destruction effects for other workers who are less skilled and educated.

The regression results considering occupational variety measures are presented in Table 5.2. Like the results presented in Table 5.1, Models 1 and 2 consider the share of population at high risk of destructive digitalization, and Models 3 and 4 the share of population with high exposure to transformative digitalization.

Looking at Models 1 and 2, we find that related occupational variety within municipalities does not significantly affect the proportion of workers at high risk of job replacement, while unrelated occupational variety shows a positive but marginally significant effect, significant only at the 10% level. These results partially confirm Hypothesis 3. Considering Models 3 and 4, it can be observed that the measures for both related and unrelated occupational variety are positive and highly significant. This implies that municipalities with greater unrelated or related occupational variety will experience an increase in the proportion of employment highly exposed to transformative digitalization, confirming Hypothesis 4.

The results for Models 1 and 2 can be explained as destructive digitalization primarily targets specific industries, in particular manufacturing, since it leads to the automation of repetitive tasks and processes (Acemoglu and Restrepo, 2020b; Dauth et al., 2021; Montobbio et al., 2022). Consequently, the impact of these technologies may be more related to the industrial structure of a region, rather than its occupational composition. This kind of technologies target specific job functions, low-skilled workers, and routine tasks (Frey and Osborne, 2017; Barbieri et al., 2019; Montobbio et al., 2022), so the variety of occupations may have a limited impact on the exposure to destructive digitalization. Also, this impact can be more targeted to specific tasks rather than broad occupational categories. Arntz et al. (2016) argue that new technologies are unlikely to fully automate occupations on a large scale but rather affect the different tasks that compose each occupation. Therefore, it is likely that different results would be obtained if it was employed a measure of relatedness between tasks in a region, instead of occupations.

Table 5.2: Estimates of mean employment share at high risk/exposure to digitalization, with related occupational variety, unrelated occupational variety and specialization of education

	(1) Destr.	(2) Destr.	(3) Transf.	(4) Transf.
Related Occupational Variety	0.012	0.012	0.035***	0.035***
	(0.011)	(0.011)	(0.007)	(0.007)
Unrelated Occupational Variety	0.026*	0.027*	0.042***	0.042***
	(0.015)	(0.015)	(0.008)	(0.008)
Specialization of education		0.061**		-0.024
		(0.031)		(0.032)
Prop. college	-0.188***	-0.201***	0.444***	0.449***
	(0.048)	(0.050)	(0.038)	(0.038)
Prop. in services	-0.164***	-0.164***	0.047***	0.047***
	(0.028)	(0.028)	(0.017)	(0.017)
Prop. Destructive$_{t-1}$	0.567***	0.565***		
	(0.045)	(0.046)		
Prop. Transformative$_{t-1}$			0.457***	0.457***
			(0.035)	(0.035)
Constant	1.351***	1.369***	-0.216	-0.223
	(0.261)	(0.261)	(0.192)	(0.192)
Observations	2780	2780	2780	2780
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.795	0.780	0.868	0.844
Hausman test p-value	0.000	0.000	0.000	0.000

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

The positive and significant result at 10% for unrelated occupational variety supports Hypothesis 3, and can be explained by the fact that regions with more diverse occupations, i.e., with a more diverse set of skills and job functions, can facilitate the integration and adoption of new technologies, even if it implies technologies with labor-replacement effects.

These results lead us to reject partially the Hypothesis 3, which states that both occupational variety measures would increase the share of workers at high risk of destructive digitalization. The argument put forth to develop this hypothesis was that both related and unrelated variety at the occupational level can be related to cognitive diversity and to the existence of knowledge spillovers between individuals, which could augment a region's capacity for innovation and subsequently increase the adoption of new technologies. However, the observed effect may be influenced by the nature of the technologies associated with destructive digitalization. Such technologies predominantly impact specific industries and tasks, so the knowledge spillovers that could arise from occupational variety in a region might not be directly linked to a region's exposure to destructive digitalization.

Considering Models 3 and 4, it can be observed that the measures for both related and unrelated occupational variety are positive and highly significant at 1% level. Acemoglu and Restrepo (2019) concluded that the job-complementing effect and the creation of new tasks that come from AI may demand a different set of skills that workers would need to acquire. This suggests that regions with higher levels of occupational variety, whether related or unrelated, may be better equipped to adopt and adapt to transformative digitalization. The emergence of new tasks facilitated by AI may require diverse skill sets, which are more readily available in regions with greater occupational variety. Therefore, regions with diverse occupational compositions are more likely to embrace transformative digitalization as they have a higher probability of possessing the necessary skills to enjoy the benefits of AI technologies.

Wixe and Andersson's (2017) results indicate that occupational related variety in a region leads to knowledge spillovers that stimulate productivity growth. Additionally, Yang (2022) establishes a positive association between AI technology and productivity. This suggests that regions with a higher proportion of employment in diverse yet related occupations may benefit from knowledge spillovers that increase their innovation capacity. Consequently, they may be more prone to incorporate new technologies, in particular AI, into their work processes, enhancing their productivity. Furthermore, in agreement with hypothesis 4, unrelated occupational variety can also lead to knowledge spillovers between individuals, promoting technological breakthroughs. The presence of occupational diversity thus facilitates a greater likelihood for the local workforce to utilize AI technologies, that can contribute positively to their productivity.

Finally, Table 5.3 contains the regression results considering all the main explanatory variables. It is important to notice that when all the main explanatory variables are included in the same model, the unrelated occupational variety for destructive digitalization remains positive, but loses its significance. As for transformative digitalization, the measure for unrelated industrial variety loses its significance. This can happen due to a lack of estimation precision, since industrial and occupational variety variables, despite capturing distinct aspects, are strongly positively correlated. The table with the Pearson correlation coefficients (significant at 1%) between these variables is presented in Table A.6 in Appendix A.

Throughout the results presented, for destructive digitalization, it can be noticed that the measure for the degree of specialization of education is positive and significant at a 5% level. This result confirms Hypothesis 5. This variable represents the concentration of college-educated individuals in specific fields of study. As so, higher values of this variable may also imply a greater degree of skill homogenization within a region. In the context of destructive digitalization, regions with more homogeneous skill sets may face increased exposure to such technologies. Skill specialization can make it more challenging for people to adapt to changing job requirements that come from automation (Montobbio et al., 2022), leading to a mismatch between available skills and new labor market demands. Consequently, workers with highly specialized skills may struggle to transition into new jobs, which increases the likelihood of them being vulnerable to the destruction effects brought by these technologies.

This result is in line with what was concluded regarding the occupational variety measures, as the lack of significant results may be explained by the fact that this kind of technologies target specific industries and tasks, and thus the variety of occupations in a region may not be linked to this increased risk of exposure. As such, instead of variety measures, a measure for specialization better captures this effect, since it is specific tasks and sets of skills that may be at risk.

Table 5.3: Estimates of mean employment share at high risk/exposure to digitalization, with all the main explanatory variables

	(1) **Destr.**	(2) **Transf.**
Related Industrial Variety	0.020*** (0.007)	0.010** (0.005)
Unrelated Industrial Variety	0.017** (0.008)	-0.000 (0.006)
Related Occupational Variety	0.004 (0.012)	0.033*** (0.007)
Unrelated Occupational Variety	0.012 (0.016)	0.040*** (0.009)
Specialization of education	0.063** (0.030)	-0.026 (0.033)
Prop. college	-0.185*** (0.051)	0.456*** (0.039)
Prop. in services	-0.174*** (0.028)	0.046*** (0.017)
Prop. Destructive$_{t-1}$	0.561*** (0.045)	
Prop. Transformative$_{t-1}$		0.455*** (0.035)
Constant	1.382*** (0.261)	-0.221 (0.191)
Observations	2780	2780
AR (1)	0.000	0.000
AR (2)	0.764	0.850
Hausman test p-value	0.000	0.000

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

Regarding transformative digitalization, it can be noted that the measure for the specialization of education is always negative, but it is never significant. This can be because AI requires a broad set of skills, due to the creation of new tasks. As such, regions with high levels of specialization of education probably have a more similar and specific set of skills, and thus the workforce may not have the necessary skills to promote significantly the adoption of transformative digitalization. This is also in line with the findings regarding the occupational variety measures, which suggested that a greater variety of occupations in general promotes a higher exposure to this type of technologies. The diverse skill sets present in regions with a greater variety of occupations can lead the workforce to adopt and adapt easily to this type of technologies.

When examining the share of college-educated workers, it can be noticed that it strongly reduces the proportion of workers at high risk of replacement, but it positively impacts the share of workers with high exposure to the benefits of AI. This effect is expected since less educated people tend to be more negatively affected by digitalization, and thus, more exposed to automation risk (Muro et al., 2019; Crowley and Doran, 2023; Arntz et al., 2016; Crowley et al., 2021). In contrast, highly educated individuals are usually involved in non-routine and highly skilled occupations, which are prioritized by AI technologies, thereby potentially subjecting them to higher levels of exposure (Felten et al., 2021; Tschang and Almirall, 2021).

Municipalities with a higher proportion of people employed in services industries show greater resilience to the adverse impacts of destructive digitalization, as evidenced by a decrease in regional exposure to job replacement. At the same time, they benefit from a greater share of workers exposed to transformative digitalization. Destructive digitalization primarily targets manufacturing sectors, which are often characterized by routine tasks (Acemoglu and Restrepo, 2020b; Humlum, 2021). Despite the negative impacts on employment in the manufacturing sector, there can exist positive and significant spillover effects into services sectors, which can lead to an increase in the total employment (Dauth et al., 2021). Consequently, a higher proportion of individuals employed in service industries face a reduced vulnerability to job replacement. According to Felten et al. (2021), exposure to AI seems to be highest for white-collar occupations and industries, typically associated with high-skilled occupations involving mental or administrative tasks rather than manual labor. Consequently, a higher proportion of people engaged in such occupations, often related to service industries, face an increased exposure to job-complementing effects brought by these technologies.

Chapter 6. Conclusion

In this thesis, we explored the regional characteristics that make employment more susceptible to either destructive digitalization or more exposed to transformative digitalization. Identifying these factors is essential for policymakers to develop effective strategies that mitigate the adverse effects of recent technological developments and facilitate the integration and adoption of technologies with positive effects.

Our findings indicate that higher levels of both unrelated and related industrial variety are significantly linked to an increase in the proportion of workers facing high susceptibility to replacement by labor-saving technologies, as well as those highly exposed to labor-augmenting technologies. This indicates that regions with greater industrial variety are more likely to leverage from knowledge spillovers that lead them to innovate and adopt new technologies, irrespective of their labor effects.

Therefore, municipalities specializing in industries more vulnerable to destructive digitalization may experience declines in employment rates and those with a greater presence of industries that benefit from transformative digitalization may witness employment and productivity growth. This could result in heightened inequality within and between municipalities, depending on their industrial composition. Such inequality may stem from routine-biased technical change, wherein digitalization reduces job opportunities for workers employed in routine tasks while augmenting prospects for those in nonroutine tasks (Goos et al., 2021). This phenomenon is in agreement with the concept of directed technological change, which argues that skilled workers, as the primary drivers of technological advancements, tend to develop technologies that favor their interests, possibly amplifying the risk of job displacement for less skilled workers (Acemoglu, 1998). To mitigate these adverse outcomes, policymakers should prioritize and invest in industrial activities, in particular service industries, that can decrease regions' susceptibility to job displacement effects while effectively leveraging the benefits of transformative digitalization.

In studying the impact of occupational variety measures, our results indicate varying effects depending on the types of technologies considered. Related occupational variety shows no significant impact on the proportion of workers at high risk of destructive digitalization, whereas unrelated occupational variety demonstrates a positive albeit marginally significant effect on regional susceptibility to such technologies. Conversely, for transformative digitalization, both measures of occupational variety lead to increased regional exposure to these technologies.

These differences can be attributed to the distinct nature of the technologies involved. Knowledge spillovers between individuals can result from occupational variety, and thus we would expect a higher adoption of every type of technology. However, destructive digitalization tends to target specific industries, jobs, and tasks. As such, the variety of occupations in a region might have a limited impact on the exposure of a region to these types of technologies. Conversely, transformative digitalization enhances productivity and introduces new tasks, requiring a diverse set of skills. Regions with higher occupational variety have a more diverse set of skills and are better positioned to leverage these effects, as they can easily adapt to the evolving demands of the technology.

These findings are supported by the results obtained for educational specialization. The results suggest that a higher specialization of education in a region leads to a higher share of workers at high risk of replacement by digitalization, but it does not significantly affect the share of the population exposed to labor-augmenting technologies. This shows that the diversity in skills and occupations is important to determine the exposure to transformative digitalization, while the homogenization of skills is more important in explaining the share of workers at high risk of destructive digitalization.

These findings show that it is important for regional development strategies to prioritize the diversification of individuals' occupations. Municipalities with greater shares of variety among occupations can leverage the resulting knowledge spillovers and become more exposed to the transformative effects of new technologies, without necessarily affecting their exposure to possible destructive effects. At the same time, they are more likely to possess the necessary skills to enjoy the benefits of AI technologies. Additionally, policy initiatives should aim to foster a broader diversification of educational fields among the population. Our research reveals that municipalities with a concentrated population in specific educational fields face heightened risks associated with destructive digitalization. Therefore, interventions that promote a more varied educational landscape can help mitigate these risks and enhance the region's overall resilience to technological disruption.

Our estimates also reveal that a region's exposure to new technologies is influenced not only by its industrial makeup but also by its occupational and educational composition. This aligns with the notion proposed by Desrochers and Leppälä (2011), suggesting that knowledge spillovers can occur at the individual level, and not just at the industry level. The relationship between agglomeration externalities at the individual level and a region's exposure to technologies is not widely explored in the literature. Therefore, the present work contributes to filling that gap, advancing our understanding of these dynamics.

This study contributes to the regional studies literature by examining how regions are exposed to technology, an area that has received little attention. The existing limited research on this topic tends to focus on technologies with labor-saving impacts, in particular automation, and does not address the potential labor-augmenting capacity of new technologies that is explored in the present dissertation. Understanding this aspect is equally important for policymakers to understand the regional characteristics that facilitate harnessing the positive impacts of new technologies.

To measure the share of employment at high risk of destructive digitalization, we employed the occupation-based approach proposed by Frey and Osborne (2017). Despite being widely used in numerous studies, different authors have argued that this measure may lead to an overestimation of job automation. This is because occupations considered to be at high risk of automation often comprise diverse tasks that can be difficult to automate (Arntz et al., 2016; Nedelkoska and Quintini, 2018). Therefore, future research in this area could explore task-based approaches proposed by Arntz et al. (2016) and Nedelkoska and Quintini (2018) to measure the exposure to labor-saving technologies. Additionally, Frey and Osborne's (2017) measure is considered forward-looking, as it relies on expectations of future technological developments. However, alternative backward-looking measures, which only consider current technological advancements, such as the one proposed by Montobbio et al. (2024), could also be employed to evaluate exposure to labor-saving automation.

For assessing exposure to transformative digitalization, we utilized a measure developed by Felten et al. (2021), that estimates the level of exposure of occupations to AI technologies. This measure, like the one used for assessing destructive digitalization, is also forward-looking. Future studies could employ a backward-looking measure developed by Felten et al. (2018). Another measure of exposure that could be applied in future research is the one developed by Kogan et al. (2023), which measures the exposure of occupations to labor-saving and labor-augmenting technology through textual analysis of patents and job tasks. By applying this measure, it would be easier to distinguish between the negative and positive effects that new technologies may have.

Future research could utilize alternative measures of regional occupational composition, like the one proposed by Hervé (2023). This measure assesses the degree of industrial specialization of an occupation using a Herfindahl index. Understanding how occupational industry specificity relates to technology exposure could provide valuable insights on this topic.

In terms of limitations, it is reasonable to consider that occupational variety measures could foster knowledge spillovers similarly to industrial variety, and thus, we would expect that these could also contribute to the population being more likely to adopt new technologies that come from being more prone to diverse forms of innovation. However, while there was only a marginally significant effect for unrelated occupational variety in the context of destructive digitalization, related occupational variety yielded no significant results. This may be due to the nature of this type of digitalization. Employing alternative measures of exposure to labor-saving technologies could yield varied results. Additionally, using a measure of task relatedness within regions, rather than occupations, might have also produced different outcomes

Additionally, the computation of educational relatedness, as done in Wixe and Andersson (2017), was not feasible due to the limited detail available in the Portuguese educational codes, which only have information on education up to a three-digit level. If more detailed codes of education were accessible, they could be used to construct a measure of educational variety and their effects could be studied.

Furthermore, it is important to note that this study focuses on Portuguese municipalities within the context of Portugal's small open economy. While the findings may apply to other smaller European economies, differences may arise in countries with distinct economic and industrial structures. Nonetheless, future research could explore the methodology applied here to study regional dynamics in other European countries, such as Belgium.

The primary finding of this study underscores the significance of regional characteristics in addressing the potential impacts of the recent automation wave. Regional studies play a central role in comprehending these effects. New technologies, particularly those associated with AI, can bring several benefits to employment and productivity, but understanding which regional characteristics facilitate these positive impacts is of utmost importance. Businesses must strategically adapt to maintain competitiveness and capitalize on transformative effects, ensuring employee well-being. Policies should be tailored to these regional characteristics for risks to be minimized while maximizing benefits.

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Appendix

Appendix A - Results and Correlation Tables

Table A.1: Estimates of mean employment share at high risk/exposure to digitalization, with related industrial variety, unrelated industrial variety and specialization of education

	(1) **Destr.**	**(2)** **Destr.**	**(3)** **Transf.**	**(4)** **Transf.**
Related Industrial Variety	0.023***	0.023***	0.022***	0.022***
	(0.008)	(0.008)	(0.005)	(0.005)
Unrelated Industrial Variety	0.020**	0.021**	0.018***	0.017***
	(0.008)	(0.008)	(0.005)	(0.005)
Specialization of education		0.061**		-0.037
		(0.029)		(0.037)
Prop. college	-0.153***	-0.165***	0.508***	0.515***
	(0.045)	(0.046)	(0.038)	(0.039)
Prop. female	-0.040	-0.038	-0.027	-0.028
	(0.056)	(0.056)	(0.028)	(0.028)
Prop. full time	0.216***	0.218***	-0.035	-0.036
	(0.075)	(0.075)	(0.043)	(0.043)
Prop. in services	-0.173***	-0.174***	0.041**	0.041**
	(0.029)	(0.029)	(0.019)	(0.019)
Prop. in medium/large establishments	0.014	0.012	-0.048***	-0.047**
	(0.024)	(0.024)	(0.014)	(0.014)
log(mean worker age)	-0.320***	-0.324***	0.015	0.017
	(0.068)	(0.068)	(0.051)	(0.051)
log(pop. density)	0.007	0.002	-0.027	-0.024
	(0.022)	(0.022)	(0.018)	(0.018)
log(mean salary)	-0.024	-0.023	0.043***	0.043***
	(0.021)	(0.021)	(0.013)	(0.013)
Prop. Destructive$_{t-1}$	0.566***	0.564***		
	(0.044)	(0.044)		
Prop.Transformative$_{t-1}$			0.491***	0.490***
			(0.035)	(0.035)
Constant	1.374***	1.394***	-0.187	-0.198
	(0.264)	(0.265)	(0.199)	(0.197)
Observations	2780	2780	2780	2780
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.790	0.774	0.907	0.867
Hausman test p-value	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 A.2: Estimates of mean employment share at high risk/exposure to digitalization, with related occupational variety, unrelated occupational variety and specialization of education

	(1) **Destr.**	**(2)** **Destr.**	**(3)** **Transf.**	**(4)** **Transf.**
Related Occupational Variety	0.012	0.012	0.035***	0.035***
	(0.011)	(0.011)	(0.007)	(0.007)
Unrelated Occupational Variety	0.026*	0.027*	0.042***	0.042***
	(0.015)	(0.015)	(0.008)	(0.008)
Specialization of education		0.061**		-0.024
		(0.031)		(0.032)
Prop. college	-0.188***	-0.201***	0.444***	0.449***
	(0.048)	(0.050)	(0.038)	(0.038)
Prop. female	-0.038	-0.036	-0.010	-0.011
	(0.056)	(0.057)	(0.026)	(0.026)
Prop. full time	0.191***	0.192***	-0.076**	-0.077**
	(0.069)	(0.068)	(0.031)	(0.032)
Prop. in services	-0.164***	-0.164***	0.047***	0.047***
	(0.028)	(0.028)	(0.017)	(0.017)
Prop. in medium/large establishments	0.001	-0.001	-0.043***	-0.042***
	(0.023)	(0.023)	(0.012)	(0.012)
log(mean worker age)	-0.322***	-0.326***	-0.002	-0.001
	(0.070)	(0.070)	(0.048)	(0.048)
log(pop. density)	0.014	0.010	-0.020	-0.018
	(0.022)	(0.022)	(0.018)	(0.018)
log(mean salary)	-0.024	-0.023	0.037***	0.037***
	(0.019)	(0.019)	(0.011)	(0.011)
Prop. Destructive$_{t-1}$	0.567***	0.565***		
	(0.045)	(0.046)		
Prop. Transformative$_{t-1}$			0.457***	0.457***
			(0.035)	(0.035)
Constant	1.351***	1.369***	-0.216	-0.223
	(0.261)	(0.261)	(0.192)	(0.192)
Observations	2780	2780	2780	2780
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.795	0.780	0.868	0.844
Hausman test p-value	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 A.3: Estimates of mean employment share at high risk/exposure to digitalization, with all the main explanatory variables

	(1) **Destr.**	**(2)** **Transf.**
Related Industrial Variety	0.020***	0.010**
	(0.007)	(0.005)
Unrelated Industrial Variety	0.017**	-0.000
	(0.008)	(0.006)
Related Occupational Variety	0.004	0.033***
	(0.012)	(0.007)
Unrelated Occupational Variety	0.012	0.040***
	(0.016)	(0.009)
Specialization of education	0.063**	-0.026
	(0.030)	(0.033)
Prop. college	-0.185***	0.456***
	(0.051)	(0.039)
Prop. female	-0.035	-0.012
	(0.057)	(0.026)
Prop. full time	0.210***	-0.073**
	(0.069)	(0.030)
Prop. in services	-0.174***	0.046***
	(0.028)	(0.017)
Prop. in medium/large establishments	0.015	-0.037***
	(0.024)	(0.012)
log(mean worker age)	-0.328***	0.002
	(0.069)	(0.048)
log(pop. density)	0.004	-0.019
	(0.022)	(0.018)
log(mean salary)	-0.025	0.035***
	(0.020)	(0.011)
Prop. Destructive$_{t-1}$	0.561***	
	(0.045)	
Prop. Transformative$_{t-1}$		0.455***
		(0.035)
Constant	1.382***	-0.221
	(0.261)	(0.191)
Observations	2780	2780
AR (1)	0.000	0.000
AR (2)	0.764	0.850
Hausman test p-value	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 A.4: Estimates of mean employment share at high risk/exposure to digitalization, using System GMM

	2-step System GMM		1-step System GMM	
	(1) **Destr.**	**(2)** **Transf.**	**(3)** **Destr.**	**(4)** **Transf.**
Related Industrial Variety	0.022***	-0.002	0.024***	-0.003
	(0.005)	(0.003)	(0.005)	(0.003)
Unrelated Industrial Variety	0.011**	-0.004	0.010*	-0.006
	(0.005)	(0.004)	(0.005)	(0.004)
Related Occupational Variety	-0.017**	0.021***	-0.018**	0.022***
	(0.008)	(0.008)	(0.008)	(0.007)
Unrelated Occupational Variety	-0.010	0.033***	-0.009	0.033***
	(0.011)	(0.008)	(0.011)	(0.008)
Specialization of education	-0.030	0.056	-0.008	0.041
	(0.040)	(0.037)	(0.040)	(0.035)
Prop. college	-0.105***	0.370***	-0.099***	0.331***
	(0.035)	(0.051)	(0.035)	(0.049)
Prop. female	0.012	0.036**	0.004	0.029*
	(0.023)	(0.018)	(0.025)	(0.017)
Prop. full time	0.092**	-0.122**	0.124***	-0.098**
	(0.043)	(0.050)	(0.046)	(0.043)
Prop. in services	-0.083***	0.052***	-0.083***	0.049***
	(0.015)	(0.010)	(0.015)	(0.011)
Prop. in medium/large establishments	-0.007	-0.059***	-0.005	-0.053***
	(0.012)	(0.011)	(0.012)	(0.010)
log(mean worker age)	-0.198***	0.021	-0.208***	0.009
	(0.047)	(0.031)	(0.047)	(0.029)
log(pop. density)	0.001	0.005***	0.002	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
log(mean salary)	-0.003	0.048***	-0.011	0.040***
	(0.015)	(0.010)	(0.016)	(0.009)
Prop. Destructive$_{t-1}$	0.640***		0.623***	
	(0.050)		(0.049)	
Prop. Transformative$_{t-1}$		0.432***		0.497***
		(0.074)		(0.072)
Constant	0.917***	-0.366***	0.986***	-0.289**
	(0.181)	(0.126)	(0.184)	(0.117)
Observations	2780	2780	2780	2780
Number of instruments	33	33	33	33
Hansen test p-value	0.605	0.036	0.605	0.036
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.871	0.833	0.882	0.727

Standard errors in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Estimates of mean employment share at high risk/exposure to digitalization, using Difference GMM

	2-step Difference GMM		1-step Difference GMM	
	(1) **Destr.**	**(2)** **Transf.**	**(3)** **Destr.**	**(4)** **Transf.**
Related Industrial Variety	0.043*** (0.011)	0.015* (0.008)	0.040*** (0.011)	0.010 (0.008)
Unrelated Industrial Variety	0.023** (0.010)	0.009 (0.010)	0.022** (0.010)	0.008 (0.009)
Related Occupational Variety	-0.021 (0.017)	0.027** (0.011)	-0.001 (0.019)	0.029*** (0.010)
Unelated Occupational Variety	0.004 (0.022)	0.051*** (0.017)	0.014 (0.023)	0.058*** (0.015)
Specialization of education	0.087** (0.044)	0.010 (0.043)	0.119*** (0.045)	0.015 (0.041)
Prop. college	-0.277*** (0.084)	0.731*** (0.067)	-0.269*** (0.084)	0.715*** (0.065)
Prop. female	-0.173*** (0.064)	0.021 (0.040)	-0.158** (0.070)	0.009 (0.037)
Prop. full time	0.260*** (0.073)	-0.135*** (0.043)	0.268*** (0.072)	-0.149*** (0.039)
Prop. in services	-0.213*** (0.036)	0.080*** (0.029)	-0.238*** (0.039)	0.071*** (0.027)
Prop. in medium/large establishments	0.028 (0.031)	-0.038** (0.019)	0.041 (0.034)	-0.038** (0.017)
log(mean worker age)	-0.416*** (0.087)	0.063 (0.077)	-0.518*** (0.096)	0.047 (0.071)
log(pop. density)	-0.035 (0.037)	0.026 (0.044)	-0.047 (0.038)	0.026 (0.044)
log(mean salary)	-0.063*** (0.023)	0.055*** (0.017)	-0.068*** (0.025)	0.058*** (0.016)
Prop. Destructive$_{t-1}$	0.534*** (0.125)		0.556*** (0.099)	
Prop. Transformative$_{t-1}$		0.492*** (0.098)		0.527*** (0.091)
Observations	2502	2502	2502	2502
Number of instruments	31	31	31	31
Hansen test p-value	0.465	0.505	0.465	0.505
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.731	0.808	0.737	0.852

Standard errors in parentheses. All models include year dummies. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Pearson correlation coefficients, significant at 1%, between the main explanatory variables

	RIV	UIV	ROV	UOV	HI
Related Industrial Variety (RIV)	1.000				
Unrelated Industrial Variety (UIV)	0.6335	1.000			
Related Occupational Variety (ROV)	0.7534	0.7716	1.000		
Unrelated Occupational Variety (UOV)	0.4519	0.6877	0.3951	1.000	
Specialization of education (HI)	-0.2849	-0.2622	-0.3046	-0.2253	1.000

Appendix B - Stata Code

Bias-corrected method of moments estimator

```
set more off, permanently
capture log close
// Delete all data and memory; start a new project
clear all
use automation_region_final.dta, clear
save automation_region_final.dta, replace
// Remove from memory any previously saved estimation results
eststo clear

// We will use as a logarithm every variable that it is not a proportion
gen log_density = ln(pop_density)
gen log_workerage = ln(worker_age)
gen log_salary = ln(wage)

// Generation of dummy time variables
g d13 = year == 2013
g d14 = year == 2014
g d15 = year == 2015
g d16 = year == 2016
g d17 = year == 2017
g d18 = year == 2018
g d19 = year == 2019
g d20 = year == 2020
g d21 = year == 2021

// Identify data as panel data
xtset region year

gen size_medium_large = size_medium + size_large

// Pearson correlation coefficients, significant at 1% level - Table A.6
pwcorr related_industrial_variety unrelated_industrial_variety
related_occupational_variety unrelated_occupational_variety
herfindahl_schooling, star(.01)
```

```
global controls college female log_workerage fulltime services log_density
size_medium_large log_salary d13-d21

// Model 1.1 - Industrial Variety + Destructive
global IV related_industrial_variety unrelated_industrial_variety
eststo highfrey_FE1: xtdpdbc high_frey $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfrey_FE1
estadd scalar serial_p2 = ‘r(p_2)’ : highfrey_FE1
eststo highfrey_RE1: xtdpdbc high_frey $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfrey_FE1
estadd scalar hausman_p = ‘r(p)’ : highfrey_FE1

// Model 1.2 - Industrial Variety + Specialization of education + Destructive
global IV related_industrial_variety unrelated_industrial_variety herfindahl_schooling
eststo highfrey_FE2: xtdpdbc high_frey $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfrey_FE2
estadd scalar serial_p2 = ‘r(p_2)’ : highfrey_FE2
eststo highfrey_RE2: xtdpdbc high_frey $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfrey_FE2
estadd scalar hausman_p = ‘r(p)’ : highfrey_FE2

// Model 1.3 - Industrial Variety + Transformative
global IV related_industrial_variety unrelated_industrial_variety
eststo highfelten_FE1: xtdpdbc high_felten $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfelten_FE1
estadd scalar serial_p2 = ‘r(p_2)’ : highfelten_FE1
eststo highfelten_RE1: xtdpdbc high_felten  $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfelten_FE1
estadd scalar hausman_p = ‘r(p)’ : highfelten_FE1

// Model 1.4 - Industrial Variety + Specialization of education + Transformative
global IV related_industrial_variety unrelated_industrial_variety herfindahl_schooling
eststo highfelten_FE2: xtdpdbc high_felten $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfelten_FE2
```

```
estadd scalar serial_p2 = ‘r(p_2)’ : highfelten_FE2
eststo highfelten_RE2: xtdpdbc high_felten $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfelten_FE2
estadd scalar hausman_p = ‘r(p)’ : highfelten_FE2

// Table for Industrial Variety Measures (Table A.1)
esttab highfrey_FE1 highfrey_FE2 highfelten_FE1 highfelten_FE2 ///
, compress nogaps ///
b(3) se(3) drop(d*) star(* 0.10 ** 0.05 *** 0.01) ///
mtitles (Destr. Destr. Transf. Transf.) ///
scalars("serial_p1 Order 1 Serial Correlation test p-value"
 "serial_p2 Order 2 Serial Correlation test p-value" "hausman_p Hausman test p-value")
order(related_industrial_variety unrelated_industrial_variety herfindahl_schooling
 college female fulltime services size_medium_large log_*) ///
title("Estimates of mean employment share at high risk/exposure to digitalization
 - Industrial Variety") ///
note("Standard errors (clustered at the municipality level) in parentheses.
 All models include year dummies.")

// Model 2.1 - Occupational Variety + Destructive
global IV related_occupational_variety unrelated_occupational_variety
eststo highfrey_FE3: xtdpdbc high_frey $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfrey_FE3
estadd scalar serial_p2 = ‘r(p_2)’ : highfrey_FE3
eststo highfrey_RE3: xtdpdbc high_frey $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfrey_FE3
estadd scalar hausman_p = ‘r(p)’ : highfrey_FE3

// Model 2.2 - Occupational Variety + Specialization of education + Destructive
global IV related_occupational_variety unrelated_occupational_variety
herfindahl_schooling
eststo highfrey_FE4: xtdpdbc high_frey $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfrey_FE4
estadd scalar serial_p2 = ‘r(p_2)’ : highfrey_FE4
eststo highfrey_RE4: xtdpdbc high_frey $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfrey_FE4
estadd scalar hausman_p = ‘r(p)’ : highfrey_FE4
```

```
// Model 2.3 - Occupational Variety + Transformative
global IV related_occupational_variety unrelated_occupational_variety
eststo highfelten_FE3: xtdpdbc high_felten $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfelten_FE3
estadd scalar serial_p2 = ‘r(p_2)’ : highfelten_FE3
eststo highfelten_RE3: xtdpdbc high_felten  $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfelten_FE3
estadd scalar hausman_p = ‘r(p)’ : highfelten_FE3

// Model 2.4 - Occupational Variety + Specialization of education + Transformative
global IV related_occupational_variety unrelated_occupational_variety
herfindahl_schooling
eststo highfelten_FE4: xtdpdbc high_felten $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfelten_FE4
estadd scalar serial_p2 = ‘r(p_2)’ : highfelten_FE4
eststo highfelten_RE4: xtdpdbc high_felten $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfelten_FE4
estadd scalar hausman_p = ‘r(p)’ : highfelten_FE4

// Table for Occupational Variety Measures (Table A.2)
esttab highfrey_FE3 highfrey_FE4 highfelten_FE3 highfelten_FE4 ///
, compress nogaps ///
b(3) se(3) drop(d*) star(* 0.10 ** 0.05 *** 0.01) ///
mtitles (Destr. Destr. Transf. Transf.) ///
scalars("serial_p1 Order 1 Serial Correlation test p-value"
 "serial_p2 Order 2 Serial Correlation test p-value" "hausman_p Hausman test p-value")
order(related_occupational_variety unrelated_occupational_variety herfindahl_schooling
 college female fulltime services size_medium_large log_*) ///
title("Estimates of mean employment share at high risk/exposure to digitalization
 - Occupational Variety") ///
note("Standard errors (clustered at the municipality level) in parentheses.
 All models include year dummies.")
```

```
// Model 3.1 - Industrial Variety + Occupational Variety + Destructive
global IV related_industrial_variety unrelated_industrial_variety
related_occupational_variety unrelated_occupational_variety herfindahl_schooling
eststo highfrey_FE5: xtdpdbc high_frey $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfrey_FE5
estadd scalar serial_p2 = ‘r(p_2)’ : highfrey_FE5
eststo highfrey_RE5: xtdpdbc high_frey $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfrey_FE5
estadd scalar hausman_p = ‘r(p)’ : highfrey_FE5

// Model 3.2 - Industrial Variety + Occupational Variety + Transformative
eststo highfelten_FE5: xtdpdbc high_felten $IV $controls, fe vce(robust) eigtol(1e-10)
estat serial
estadd scalar serial_p1 = ‘r(p_1)’ : highfelten_FE5
estadd scalar serial_p2 = ‘r(p_2)’ : highfelten_FE5
eststo highfelten_RE5: xtdpdbc high_felten $IV $controls, re vce(robust) eigtol(1e-10)
estat hausman highfelten_FE5
estadd scalar hausman_p = ‘r(p)’ : highfelten_FE5

// Final Table (Table A.3)
esttab highfrey_FE5 highfelten_FE5 ///
, compress nogaps ///
b(3) se(3) drop(d*) star(* 0.10 ** 0.05 *** 0.01) ///
mtitles (Destr. Transf.) ///
scalars("serial_p1 Order 1 Serial Correlation test p-value"
 "serial_p2 Order 2 Serial Correlation test p-value" "hausman_p Hausman test p-value")
order(related_industrial_variety unrelated_industrial_variety
 related_occupational_variety unrelated_occupational_variety herfindahl_schooling
 college female fulltime services size_medium_large log_*) ///
title("Estimates of mean employment share at high risk/exposure to digitalization
 - Industrial and Occupational variety") ///
note("Standard errors (clustered at the municipality level) in parentheses.
 All models include year dummies.")
```

Generalized method of moments estimator

```
global IV related_industrial_variety unrelated_industrial_variety
related_occupational_variety unrelated_occupational_variety herfindahl_schooling
college female log_workerage fulltime services log_density size_medium_large
log_salary d13-d21

// System GMM two-step
global GMM L(1).high_frey
eststo highfrey_Sys2: xtabond2 high_frey $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV, equation(level)) twostep robust small

global GMM L(1).high_felten
eststo highfelten_Sys2: xtabond2 high_felten $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV, equation(level)) twostep robust small

// System GMM one-step
global GMM L(1).high_frey
eststo highfrey_Sys1: xtabond2 high_frey $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV, equation(level)) robust small

global GMM L(1).high_felten
eststo highfelten_Sys1: xtabond2 high_felten $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV, equation(level)) robust small

// Table for System GMM (Table A.4)
esttab highfrey_Sys2 highfelten_Sys2 highfrey_Sys1 highfelten_Sys1 ///
, compress nogaps ///
b(3) se(3) mtitles(Destr. Transf. Destr. Transf.)
 drop(d*) star(* 0.10 ** 0.05 *** 0.01)
scalars("j Nr. of instruments" "hansenp Hansen stat. p-value"
 "ar1p AR(1) stat. p-value" "ar2p AR(2) stat. p-value") ///
order(related_industrial_variety unrelated_industrial_variety
 related_occupational_variety unrelated_occupational_variety herfindahl_schooling
 college female fulltime services size_medium_large log_*) ///
title("System GMM estimates") ///
note("Standard errors in parentheses. All models include year dummies.
 Instruments collapsed to avoid instrument proliferation.")
```

```
// Difference GMM two-step
global GMM L(1).high_frey
eststo highfrey_Diff2: xtabond2 high_frey $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV) noleveleq twostep robust small

global GMM L(1).high_felten
eststo highfelten_Diff2: xtabond2 high_felten $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV) noleveleq twostep robust small

// Difference GMM one-step
global GMM L(1).high_frey
eststo highfrey_Diff1: xtabond2 high_frey $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV) noleveleq robust small

global GMM L(1).high_felten
eststo highfelten_Diff1: xtabond2 high_felten $GMM $IV, gmmstyle($GMM, collapse)
ivstyle($IV) noleveleq robust small

// Table for Difference GMM (Table A.5)
esttab highfrey_Diff2 highfelten_Diff2 highfrey_Diff1 highfelten_Diff1 ///
, compress nogaps ///
b(3) se(3) mtitles(Destr. Transf. Destr. Transf.)
 drop(d*) star(* 0.10 ** 0.05 *** 0.01)
scalars("j Nr. of instruments" "hansenp Hansen stat. p-value"
 "ar1p AR(1) stat. p-value" "ar2p AR(2) stat. p-value") ///
order(related_industrial_variety unrelated_industrial_variety
 related_occupational_variety unrelated_occupational_variety herfindahl_schooling
 college female fulltime services size_medium_large log_*) ///
title("Difference GMM estimates") ///
note("Standard errors in parentheses. All models include year dummies.
 Instruments collapsed to avoid instrument proliferation.")
```

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