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Master's Thesis

"Occupational Characteristics as Indicators of Employment across Europe"

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ABSTRACT

The impact of automation on labor markets has become a central topic in economic and sociopolitical discourse. This thesis investigates the influence of occupational characteristics on employment trajectories within the European Union from 2012 to 2021. By employing a dual approach that includes a comprehensive descriptive analysis and the application of a Linear Mixed Model (LMM), this study aims to identify key variables affecting employment levels across occupations. Data is sourced from the European Union Labour Force Survey (EU-LFS) and the Joint Research Centre (JRC) of the European Commission. Our findings suggest that the adoption of advanced technologies, specifically Information and Communication Technology (ICT) tools, positively correlates with employment variation rates across different sectors. Conversely, the use of machines and engagement in repetitive tasks are associated with negative impacts on employment.

Keywords: automation, labor market, job displacement, occupations, Europe.

Github: https://github.com/anaperezbarrera/Masters-Thesis

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INTRODUCTION

Automation may be defined as the use of technology to perform tasks in which human intervention is minimized. In the context of the labor market, modern theoretical economic models emphasize that new technology can both complement and/or substitute labor (Autor et al. 2003, Acemoglu and Autor, 2010). Consequently, the implications of automation depend largely on whether a particular technology predominantly replaces or complements labor and what type of worker is primarily affected (Gallego and Kurer, 2022).

For some time now, concerns about the future of the labor market in the face of automation are being increasingly addressed in the academic literature. Evidence from research indicates that technological advancements have the potential to displace workers, particularly those in manual or low-skilled occupations (Gallego and Kurer, 2019). Moreover, task displacement due to automation is estimated not only to reflect changes in labor demand, but also to have adverse effects on employment (Acemoglu and Restrepo, 2022).

Therefore, one way of assessing whether automation is a likely source of job displacement, is to analyze the employment trajectories of occupations. This will involve studying whether various occupational characteristics, particularly those related to automation, are associated with different employment outcomes in Europe, which may help to identify which types of occupations are likely to grow, shrink or potentially disappear in the labor market.

In this context, our analysis is aimed at identifying relevant variables influencing employment levels through two approaches: 1) an exhaustive descriptive analysis of the data, and 2) the application of a Linear Mixed Model (LMM). The analysis covers the period from 2012 to 2021 and utilizes data from two sources: Labor Force Survey and Joint Research Center of the European Commission. Our study reveals that the adoption of advanced technologies and the nature of work impact employment outcomes, more specifically, the employment variation rate by sector. Exposure to ICT tools has a positive impact on employment variation across various sectors, while the use of machines and engagement in repetitive tasks are associated with negative impacts on employment. Despite these results, the explanatory power of our models remains moderately low, a limitation that stems from several factors inherent in our dataset.

I. LITERATURE REVIEW

The existing debate on the differential impact of technology on employment, productivity and income inequality suggests that more attention needs to be paid to the impact of automation in the workplace. For instance, Acemoglu and Restrepo (2022) argued that a significant portion of the rise in U.S. wage inequality over the last four decades has been driven by automation, whereas others suggest that new technologies could create new employment opportunities and mitigate some of these inequalities (Vermeulen et al., 2018).

The McKinsey Global Institute (2017) estimates that up to 375 million workers globally may need to transition to new occupational categories due to rapid automation adoption, arguing that more occupations will change rather than be lost as machines affect portions of occupations and people increasingly work alongside them. At the occupational level, Gallego and Kurer (2019) point out that the benefits of technological advances are disproportionately enjoyed by non-routine or highly skilled workers in cognitively demanding jobs. In that sense, there are still many areas, particularly those requiring complex problem-solving and human interaction, where machines cannot yet replace humans (Chui et al., 2016).

While there are numerous studies on the impact of automation on the labor market in general (Acemoglu and Autor, 2010; Autor et al., 2003; Autor, 2022; Gallego and Kurer, 2019, 2022), I attempt to address its impact on employment. More specifically, on employment variation rates across occupations. Following Georgieff and Hyee (2021), it is useful to think of AI-driven automation as having two possible, but opposite, effects on employment. On the one hand, AI can reduce employment through automation/substitution. On the other hand, it can boost employment by increasing worker productivity. This thesis focuses on the latter.

Therefore, a relevant aspect, and certainly more precise for this paper, is the role of the so-called *augmentation innovations*, i.e., technologies or advancements that enhance human capabilities rather than replacing them. Building on his previous work, Autor et al. (2021) in Autor (2022), document that these innovations spur employment growth in the occupations most exposed to them. This concept resonates with Schumpeter's (1950) notion of *creative destruction*, according to which the introduction of new technologies inevitably disrupts existing industries, creating winners and losers. Those tied to older technologies may face challenges, while those working with emerging technologies will eventually benefit.

The McKinsey Global Institute (2017) assumes that all professions, whether high-skilled or unskilled, have some potential for automation, including senior executives, estimating that around 25 per cent of work is automatable. On the other hand, Arntz et al., (2016) argue that many tasks within jobs are more difficult to automate than initially assumed, as tasks often require human flexibility, creativity, and social intelligence, suggesting that the potential for job displacement may be significantly lower than previously predicted. In that sense, the distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labor market conditions and technology (Acemoglu and Autor, 2010).

These patterns indicate that new job creation may be polarized, reflecting (and partly driving) aggregate employment polarization (Autor, 2022). Workers displaced by technological change cannot find demand for their skills, probably falling into long-term unemployment or a sequence of short-term low-pay jobs with periods of unemployment in between. Conversely, innovation fosters the complementarities between technology and skills, favoring the employment and wages of the high-skilled workers (Silva and Lima, 2017).

Oesch (2006) addressed the increasing heterogeneity within the occupational system, re-defining the social class schema to integrate these shifts in the employment structure (mainly focusing on the difference in the worklogic of various occupational groups). The author argues that depending on the importance of an employee's marketable skills, employers will offer a more or less advantageous employment relationship in order to obtain maximal productivity from their personnel. In this sense, as advanced technologies are increasingly integrated into the workplace, the ability of employees to adapt and excel in roles requiring advanced skills becomes crucial to their employability and job security.

II. THE DATA

This analysis uses longitudinal data from the EU Labour Force Survey (EU-LFS), a large household sample survey providing quarterly and yearly results on labor participation of people inside and outside the labor force. Variables related to labor market participation and working conditions, including working hours and working time arrangements, were selected and calculated at the occupational level.

Moreover, data from the European Database of Task Indices provided by the Joint Research Centre (JRC) of the European Commission (2021) was incorporated in the analysis. This database builds a taxonomy of tasks according to the content of work, methods and tools employed at the workplace, where experts evaluate the importance of many different task and skill categories across different occupations, assigning standardized scores to each item (Bisello et al., 2021).

The JRC was developed using most recent data from European Working Conditions Survey (EWCS 2015), a European (Italian) version of the O*NET database of occupational contents (ICP 2012) and the OECD´s PIAAC Survey. Although EU-LFS data are available since 2006, this thesis analyzes only labor market data from 2012 to 2021 because JRC relies on these 3 databases which only refer to this time frame.

In addition, the International Labour Organisation revised in 2009 the previous version of the International Standard Classification of Occupations (ISCO), which was implemented in 2011 and: 1) places more emphasis on occupations related to information and communication technologies, and 2) is more detailed than the previous version in specific occupations in which a high share of women work (European Commission, 2009). In this paper, the 2-digit ISCO-08 version was used, which covers a total of 40 occupations.

Finally, the data are applicable to the whole EU15 (minus the UK), which includes the following countries: Austria, Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, The Netherlands, Norway, Portugal, and Sweden. Since the JRC database covers the entire EU15 without differentiating by country, possible differences between the task contents, methods and tools across different countries are missing from the database. However, the model accounted for this variation by incorporating the EU-LFS variables, which take into account these differences at the occupational level.

Table 1. Main independent variables

JOINT RESEARCH CENTER	EU-LABOR FORCE SURVEY[1]
In terms of the tasks content Physical tasks Social tasks Intellectual tasks	**Labor market participation** Home-work ratio Full-time ratio Ratio of supervisory responsibilities
In terms of the methods Autonomy Teamwork Routine	**Working conditions** Ratio of overtime or extra hours Ratio of shift types (evening, night, saturday, sunday)
In terms of the tools Machines ICT Basic ICT Advanced ICT	**Other characteristics** Ratio of female participation

This taxonomy (JRC) provides information on some attributes of work activity, and the direct effect of automation on the content of work, and indirectly through the methods and tools used. The task content dimension makes a threefold differentiation between physical tasks, whose purpose is the physical manipulation of material things; intellectual tasks, whose purpose is the transformation of information and active problem solving; and social tasks, whose main purpose is the interaction with other people. The methods category essentially refers to the forms of work organizations: autonomy of workers in their tasks, teamwork, and routine, i.e. the degree of repetitiveness and standardization of their work processes. Finally, the tools used in the workplace, in which we can distinguish between: Machines: non-digital (analog) machines; ICT: digitally enabled machines (non-autonomous computing devices); basic ICT: generic office applications; and advanced ICT: programming tools.

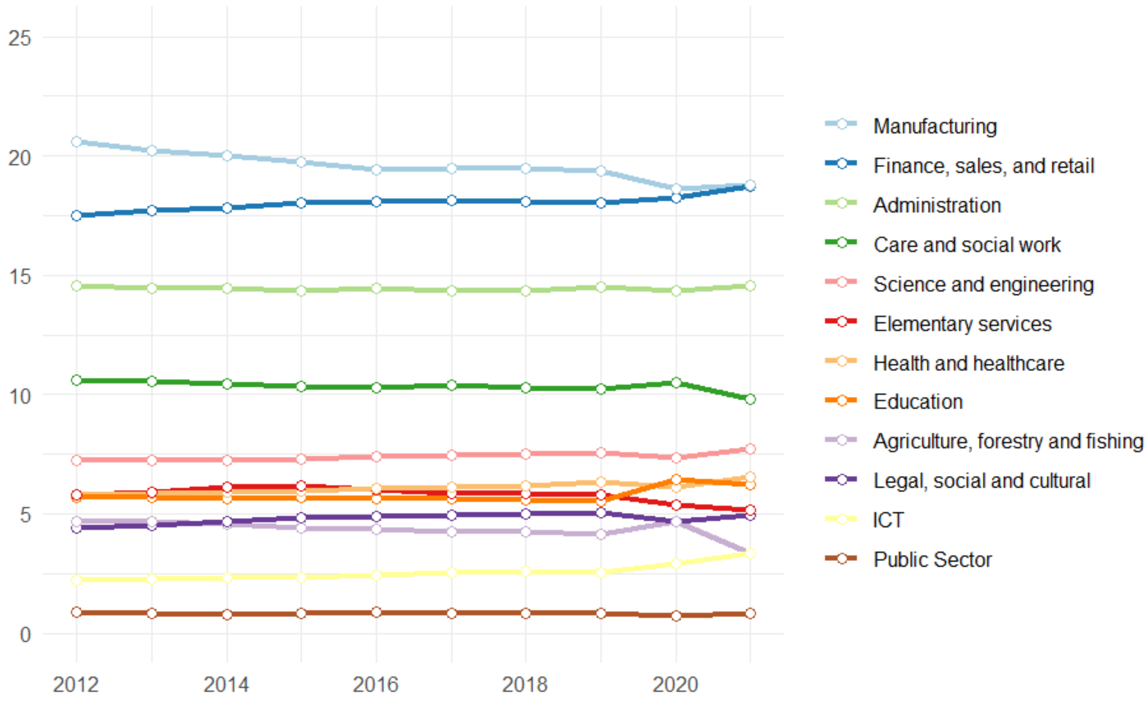
III. OCCUPATIONS AND EMPLOYMENT IN EUROPE: DESCRIPTIVE RESULTS

The evolution of employment in Europe during the reference period has been markedly uneven. Some sectors experienced significant declines in employment, particularly in 2020 and 2021, while others saw minimal job losses. To produce more aggregated data, occupations have been grouped into 12 sectors according to the main activity they perform

[1]Ratios were created at the occupational level by country and year to define occupational characteristics. These ratios range from 0 to 1. i.e, The home-work ratio refers to the proportion of workers in a specific occupation who work from home in a given year and country: 0 (part-time) to 1 (full-time).

(see Appendix 1). Figure 1 highlights two significant trends in sectoral employment: 1) the sectors that account for the largest share of total employment (construction and finance); and 2) the sectors that have experienced the greatest growth (education and technology) and decline (construction) in employment shares over recent years.

Figure 1. Yearly evolution of the employment share by sector.

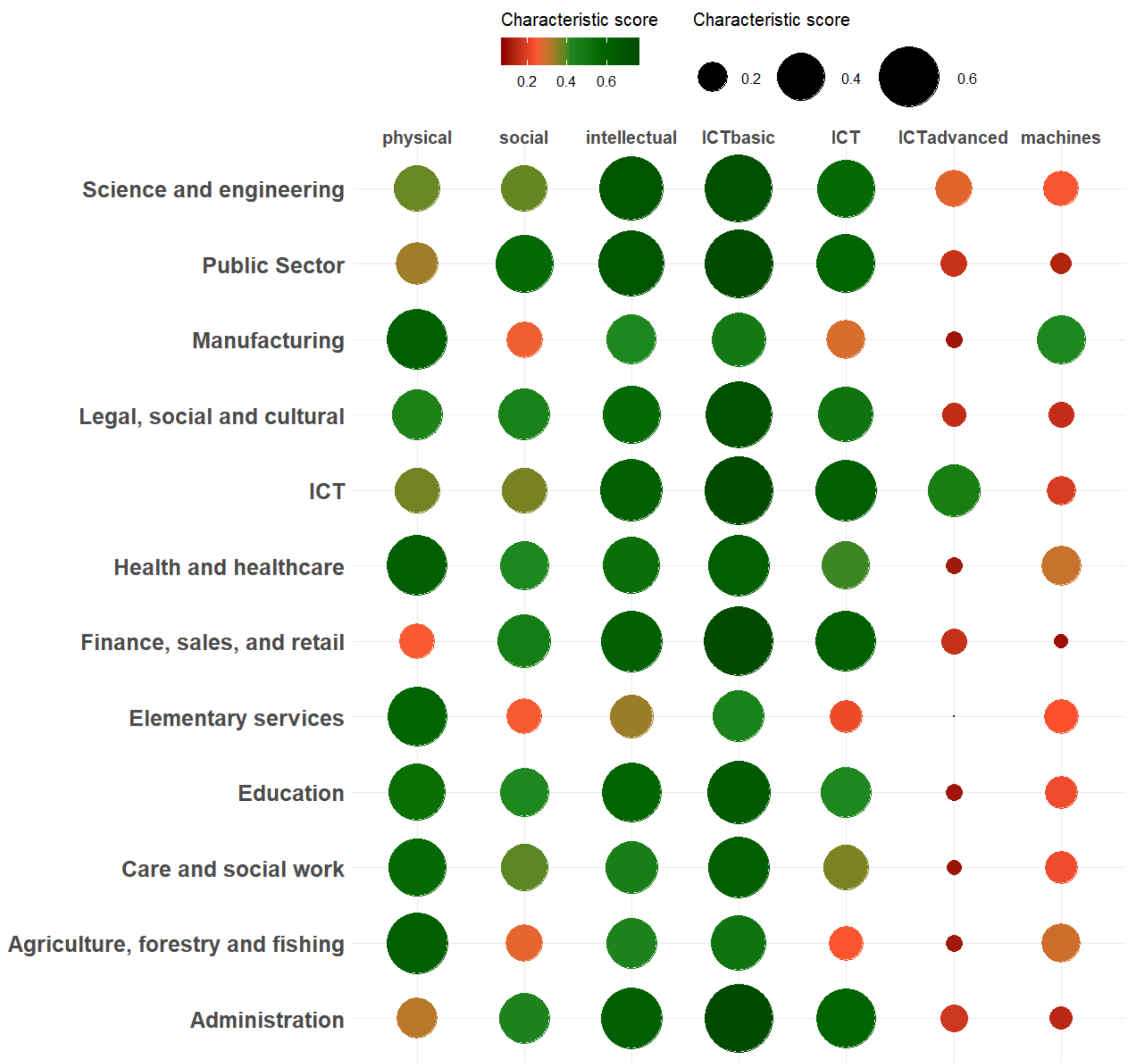


Source: own elaboration with data from LFS.

Since the 1970s, the employment share of manufacturing sectors has been decreasing in major European economies (Klenert et al., 2023). In this sector, there are occupations that have a large proportion of physical activities in predictable environments that are more vulnerable to automation (Manyika et al., 2017), suggesting that technological progress may have been much faster in manufacturing. The agricultural and elementary services, which predominantly involve physical tasks and limited use of technological tools, have also experienced declines (see Figure 1). Conversely, the ICT sector has increased its share of total employment, although it still only represents 2.5%.

The impact of AI on the labor market of a given occupation is likely to depend on the task composition of that occupation. The taxonomy of tasks from JRC (see Table 1) provides a framework for defining occupational characteristics, mainly focusing on the job content, methods, and tools. Considering that jobs are coherent sets of interrelated characteristics that cannot be adequately understood in isolation, Figure 2 represents the average scores of relevant characteristics, where: 1) intellectual, physical, and social tasks, along with basic computer use (Basic ICT), show consistent scores across sectors; and 2) specific characteristics, such as programming tools (Advanced ICT) and analog machines, exhibit uneven distribution, where the ICT and manufacturing sectors, demonstrate higher prevalence of these dimensions, respectively.

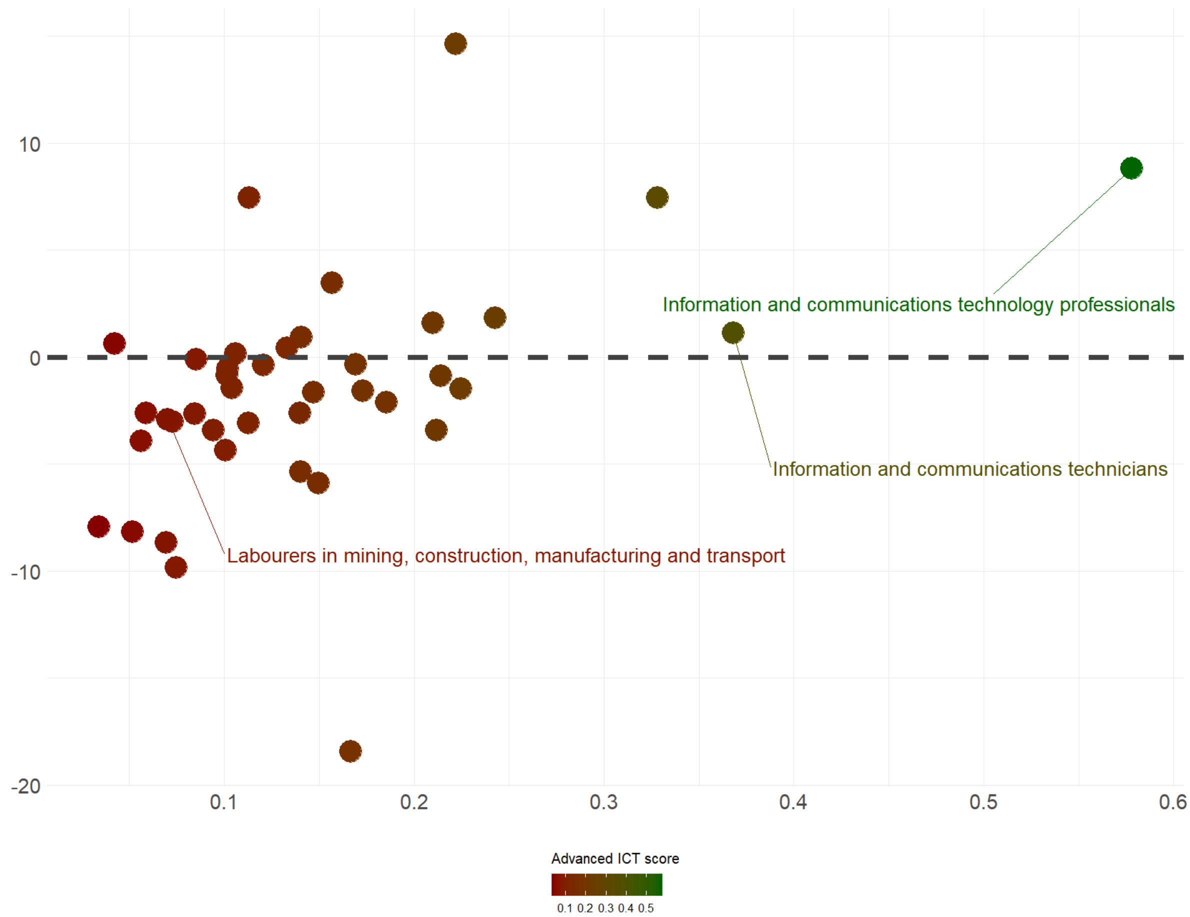
Figure 2. Taxonomy of tasks across sectors of activity.



Source: own elaboration with data from JRC.

The objective of this analysis is to determine which types of occupational characteristics are associated with different employment outcomes, particularly in relation to technological progress. Therefore, we focused on the most significant characteristics depicted in Figure 2 - Advanced ICT and analog machines - and examined their relationship with employment variations across occupations. In the United Kingdom and the United States, for instance, highly exposed occupations to computer use tend to have experienced higher employment growth, whereas occupations with low or negative employment growth had relatively low exposure to AI (Georgieff and Hyee, 2021). A similar trend is observed across European occupations (Figure 3), where employment increased in the most ICT-intensive occupations between 2012 and 2021, and decreased in the manufacturing sector

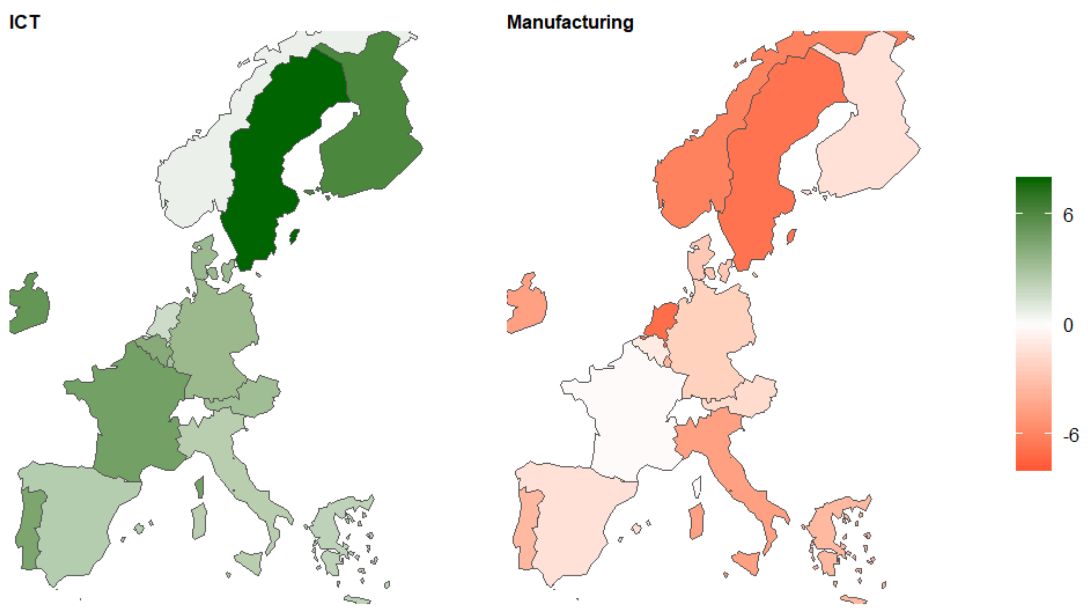
Figure 3. Use of Advanced ICT and employment rate variation across occupations (2012-2021)



Source: own elaboration with data from LFS and JRC.

These employment trajectories are also consistent across European countries. Figure 4 illustrates the employment rate variation from 2012 to 2021 for ICT professionals and the manufacturing industry, respectively. In the ICT sector, most countries have seen a growth in employment, with Sweden experiencing the most significant gain, followed by Finland, France, and Ireland. In contrast, the manufacturing industry presents a very different picture, with widespread job losses, particularly in Sweden, Norway, and Belgium. From a geographical perspective, advanced economies are likely to implement automation earlier than many emerging economies, largely due to higher wage levels that make the business case for implementation stronger (Manyika et al., 2017).

Figure 4. Cross-country differences in employment rate variation between ICT professionals and manufacturing industry (2012-2021).



Source: own elaboration with data from LFS.

IV. OCCUPATIONS AND EMPLOYMENT IN EUROPE: METHODOLOGY

1. The target variable

There are a variety of ways to measure employment (e.g., employment rate, labor force participation rate, employment growth, the likelihood of unemployment, etc.) . In 1976, the US Commissioner on Labor Statistics questioned if economists should measure the doughnut (employment) or the hole (unemployment) (Brandolini and Viviano, 2018). Indeed, indicators such as unemployment and employment rates are convenient because they are simple and easy to communicate (albeit at the cost of overlooking many complexities of labor markets).

Klenert et al. (2023), for instance, assessed the relationship between robot adoption and employment in Europe, noting that EU-LFS data can exhibit significant year-to-year variability, particularly when focusing on specific sectors or employment categories, which can pose challenges due to the short-term fluctuations that obscure long-term trends. This is why, apart from yearly data, they also look at six-year averages, which smoothes out most of the short-term fluctuations, and long-difference estimators.

In this analysis, the target variable was obtained using the EMPSTAT variable from the EU-LFS, which captures the employment status of respondents aged between 15 and 89 years. For individuals outside this age range, the EMPSTAT variable is marked as 'not applicable'. Then, it categorizes respondents as either employed or not employed. The former are our subject of interest, and the target variable is specified as follows: the annual variation in the employment share of a specific sector. Throughout this analysis, it was suggested that occupations with the greatest exposure to ICT have not only experienced significant employment growth across Europe, but have also outpaced employment gains in other sectors. This trend may highlight the growing demand for ICT skills and the role of technology-driven occupations in the European labor market. As a result, we hypothesize that the implementation of ICT tools have driven employment growth across sectors in Europe.

2. Regression Methods

The first part of this section fits an *Ordinary Least Squares* (OLS) regression, often called linear regression, which is employed controlling for country-specific and temporal effects. However, our data exhibits a hierarchical structure, where employees are nested within occupations, and occupations are nested within countries and years, i.e., multiple levels of grouping. Therefore, the second part of this section fits two *Linear mixed models* (LMM), also known as multilevel, which allow to include both fixed and random effects. The decision to use one statistical model or another is complex and often subjective; however, LMMs can simultaneously model both effects, offering flexibility in handling this type of data structures.

The regularization technique known as *lambda* (or Lasso regression) was employed for variable selection. This method helps in identifying significant predictors by penalizing less important variables, thereby preventing overfitting and improving model performance.

One the one hand, *fixed effects* provide a way to account for specific variables that remain constant across observations. This is the case of our predictors from the JRC, which are constant across countries and years. These variables are treated as fixed effects, meaning the model estimates one coefficient for each predictor that applies across all groups. By introducing occupation-level fixed effects, the model effectively controls specific characteristics to each occupation. These fixed effects capture the unique attributes that are inherent to individual occupations but remain constant across observations within each country, allowing to isolate the impact of our predictor variables while accounting for the consistent, unobserved differences.

Conversely, *random effects* account for the variability between distinct entities within the larger group. The levels in a random effect are not treated as separate and independent, but rather as representative samples from a larger collection of levels, some of which may not even be observed. By including random effects, the unique variations at each level of our data hierarchy can be modeled, such as differences between occupations, countries, and years. This is the case of our predictors from EU-LFS.

V. RESULTS AND DISCUSSION

This research aimed at investigating the role of occupational characteristics in determining employment outcomes across Europe. More particularly, our hypotheses suggested that the presence of ICT tools in the workplace is associated with higher employment growth. The first OLS (1) regression did not control for any parameters, whereas the other models (OLS(2 and 3)) did control for country-specific and temporal effects. Table 2 shows the results for the main predictors (in terms of the tools and content). The results can be interpreted as moving from one unit in the score of the predictor variable leading to a variation in the sectoral employment share, holding all other variables constant.

The findings indicate that as the score for analog machines increases by one unit, there is a corresponding negative impact on the response variable. A similar trend is observed in the estimate for repetitive tasks. This may suggest that machines might replace certain tasks traditionally performed manually, potentially reducing the proportion of employees engaged in those activities. Conversely, increased adoption of advanced ICT is positively linked to changes in employment share, suggesting that higher levels of ICT adoption are associated with greater gains in employment. The findings remain the same when controlling for country-sector- and time-fixed effects. It should be noted that the explanatory power of the three models is relatively low (approximately 30%). This is mainly due to the fact that we are not measuring the absolute employment share, but rather the change in employment share by sector over time. As these changes are often small and incremental, the models have limited ability to capture such variations accurately.

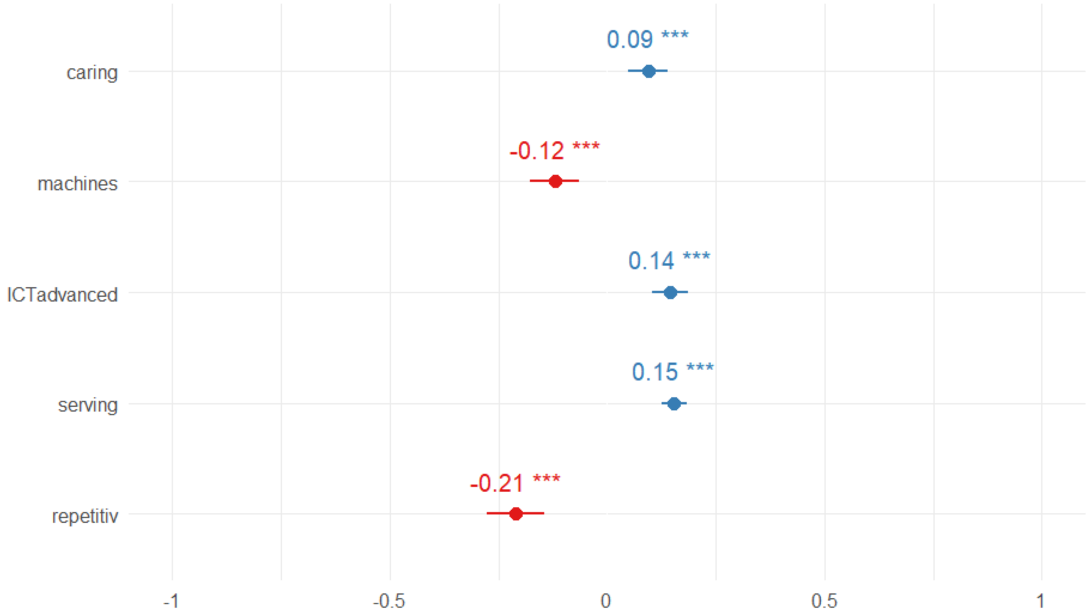
Table 2. Estimates of the independent variables on the employment share variation (2012-2018).

	Dependent variable: empchange		
	OLS (1)	OLS (2)	OLS (3)
femratio	0.079***	0.082***	0.082***
	(0.011)	(0.011)	(0.010)
serving	0.155***	0.155***	0.156***
	(0.016)	(0.016)	(0.016)
caring	0.090***	0.087***	0.087***
	(0.026)	(0.026)	(0.026)
repetitiv	−0.209***	−0.212***	−0.212***
	(0.037)	(0.037)	(0.036)
machines	−0.118***	−0.114***	−0.113***
	(0.032)	(0.032)	(0.032)
ICTadvanced	0.145***	0.147***	0.147***
	(0.023)	(0.023)	(0.022)
as.factor(COUNTRY)		✓	✓
YEAR		0.004***	
		(0.001)	
as.factor(YEAR)			✓
Constant	−0.090***	−7.604***	−0.060***
	(0.019)	(1.780)	(0.020)
Observations	4,091	4,091	4,091
R^2	0.261	0.264	0.306
Adjusted R^2	0.260	0.260	0.302
Residual Std. Error	0.113 (df = 4084)	0.113 (df = 4069)	0.110 (df = 4064)
F Statistic	239.917*** (df = 6; 4084)	69.560*** (df = 21; 4069)	68.977*** (df = 26; 4064)

Note: *p<0.1; **p<0.05; ***p<0.01

Subsequently, two LMMs are tested against each other: the simple LMM (1) incorporates random intercepts for years, allowing it to account for differences in the baseline response. On the other hand, the sophisticated LMM (2) includes a random intercept for years but extends its flexibility by introducing random intercepts and varying slopes for specific predictors of the EU-LFS (in this case, female ratio). Additionally, a custom optimization approach which adjusts how the models estimate parameters was included. In LMMs, the variance components indicate how much of the variability in the target variable is attributed to the random effects. In both models, the year has a variance of zero, suggesting that it is not contributing significantly to the variability in the employment outcomes. On the other hand, interpreting the fixed effects involves understanding how each predictor contributes to explaining the variation in the response variable.

Figure 5. Fixed effects of the Linear Mixed Model (2).



The estimates shown in Figure 5 illustrate the expected change in employment for each one-unit increase in the respective predictor variable, assuming all other variables remain constant. The analysis reveals that advanced ICT tools, which encompass programming and other technological applications, positively influence employment across various sectors. Similarly, roles that involve serving, which entails directly responding to public or customer demands, and caring, which focuses on attending to the welfare needs of others, also show a positive contribution to employment levels. Conversely, the use of machines and the prevalence of repetitive tasks are associated with a decline in employment. This suggests that while technology and social-oriented tasks drive job growth, the automation and mechanization of routine tasks may reduce the demand for human labor in these areas.

1. Evaluation and Robustness

To ensure that our predictive models are not influenced by the unique conditions of the COVID-19 pandemic, the data from 2020 was initially excluded. Instead, the dataset was divided into a training (2012-2018) and a testing (2019) set. This division allows us to train our models on historical data and validate their performance on a separate, recent dataset.

The prediction performance of these models are compared against each other using various evaluation metrics to identify the most accurate: RMSE measures the average difference between a statistical model's predicted values and the actual values; MAE measures the average magnitude of the errors in a set of predictions, without considering their direction; R-squared indicates the proportion of the variance in the dependent variable that is explained by the independent variables in the model. For mixed models or models with random effects, both marginal R^2 (explaining variance by fixed effects) and conditional R^2 (explaining variance by both fixed and random effects) can be considered. Finally, analyzing the residuals (difference between observed and predicted) can also provide insights into the model's fit.

Table 3. Comparison of model metrics for prediction.

MODEL	RMSE	R2	MAE
OLS (1)	0.080	0.37	0.061
OLS (2)	0.077	0.37	0.061
LMM (1)	0.083	0.32	0.059
LMM (2)	0.079	0.32	0.060

As previously mentioned, the explanatory capacity of our models remains moderately low, potentially due to various factors related to the structure of our data, such as limited variability in the predictors or challenges in accurately measuring employment across multiple levels. We also performed k-fold cross-validation, whose purpose is to robustly evaluate the performance and generalizability of our model. By dividing the dataset into 10 subsets (folds) and iteratively training and validating the model on different combinations of these subsets, we mitigate the risk of overfitting and ensure that our performance metrics reflect the model's predictive accuracy across varying data samples. In this case, the explanatory power (R2) of our LMM(2) increases up to 39%, which means the k-fold cross-validation successfully improved the predictive capacity of our model.

VI. LIMITATIONS AND CONCLUSIONS

One notable limitation of this study is the exclusion of the COVID-19 pandemic as a factor in our analysis. The year 2020 witnessed a widespread fall in employment levels. In contrast, 2021 showed a significant increase in employment levels, where the adoption of new technologies in various economic sectors accelerated during this period, which is not fully captured in our analysis. Another limitation is that the predictors used by JRC lack variability across countries and years. Therefore, the analysis assumes that these predictors apply consistently across different regions and time periods, which could potentially oversimplify the impact of occupational characteristics on employment trends.

Our findings indicate that using machines and performing repetitive tasks are negatively associated with employment, indicating that automation and mechanization may reduce the demand for labor in these areas.In contrast, advanced technologies and social occupations tend to have experienced higher employment growth. This trend highlights the importance of marketable skills, as argued by Oesch (2006), in response to the changing employment structure. Indeed, for sustainable growth to occur, rather than having a massive excess of labor, everyone needs to keep working alongside the robots (Manyika et al., 2017).

In contemplating the trajectory of the labor force, one cannot help but wonder whether it will conform to the prevailing "end of work" narrative or whether it will instead be shaped by profound structural changes driven by automation. Ultimately, this research was an attempt to contextualize the taxonomy of tasks, methods and tools with the employment trajectories of occupations. As observed, tasks are not isolated forms of labor inputs that just happen to be in productive processes, but building blocks of coherently constructed jobs which are embedded in productive organizations (Bisello et al., 2021).

Finally, future research would surely benefit from addressing various gaps in the literature, as suggested by Gallego and Kurer (2022). One is to contribute more explicitly to comparative empirical work. The strong reliance on US labor economics literature might obscure important variations, as the findings of significant studies examining distributive implications in the US labor market cannot be blindly applied to other countries and world regions. Additionally, female occupational trajectories in increasingly automated and digitalized labor markets differ systematically from male trajectories but have hardly been studied so far. Similarly, studying employment trajectories on exclusive levels of the occupational structure, such as the low-skilled sector, would provide valuable insights into the distinct impacts of automation on various segments of the labor market.

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APPENDIX

Appendix 1. Table of occupations grouped by sectors of activity

OCCUPATIONS BY SECTOR	
Administration	**Education**
Administrative and commercial managers	Teaching professionals
Customer services clerks	**Elementary services**
General and keyboard clerks	Cleaners and helpers
Hospitality, retail and other services managers	Food preparation assistants
Numerical and material recording clerks	Refuse workers and other elementary workers
Other clerical support workers	Street and related sales and service workers
Production and specialised services managers	**Finance, sales, and retail**
Agriculture, forestry and fishing	Business and administration associate professionals
Agricultural, forestry and fishery labourers	Business and administration professionals
Market-oriented skilled agricultural workers	Sales workers
Market-oriented skilled forestry, fishery and hunting workers	**Health and healthcare**
Subsistence farmers, fishers, hunters and gatherers	Health associate professionals
Care and social work	Health professionals
Personal care workers	**Information Technology and Digital Communications**
Personal service workers	Information and communications technicians
Protective services workers	Information and communications technology professionals
Construction, manufacturing and transport	**Legal, social and cultural**
Assemblers	Legal, social and cultural professionals
Building and related trades workers, excluding electricians	Legal, social, cultural and related associate professionals
Drivers and mobile plant operators	**Public Sector**
Electrical and electronic trades workers	Chief executives, senior officials and legislators
Food processing, wood working, garment and other craft and related trades workers	**Science and engineering**
Handicraft and printing workers	Science and engineering associate professionals
Labourers in mining, construction, manufacturing and transport	Science and engineering professionals
Metal, machinery and related trades workers	
Stationary plant and machine operators	