Master's degree in Computational Social Sciences
Academic Year 2023-2024
Master's Thesis

Occupational Characteristics as Indicators of Employment across Europe

Ana Pérez Barrera
Supervisor: Margarita Torre Fernández
Madrid, July 2024

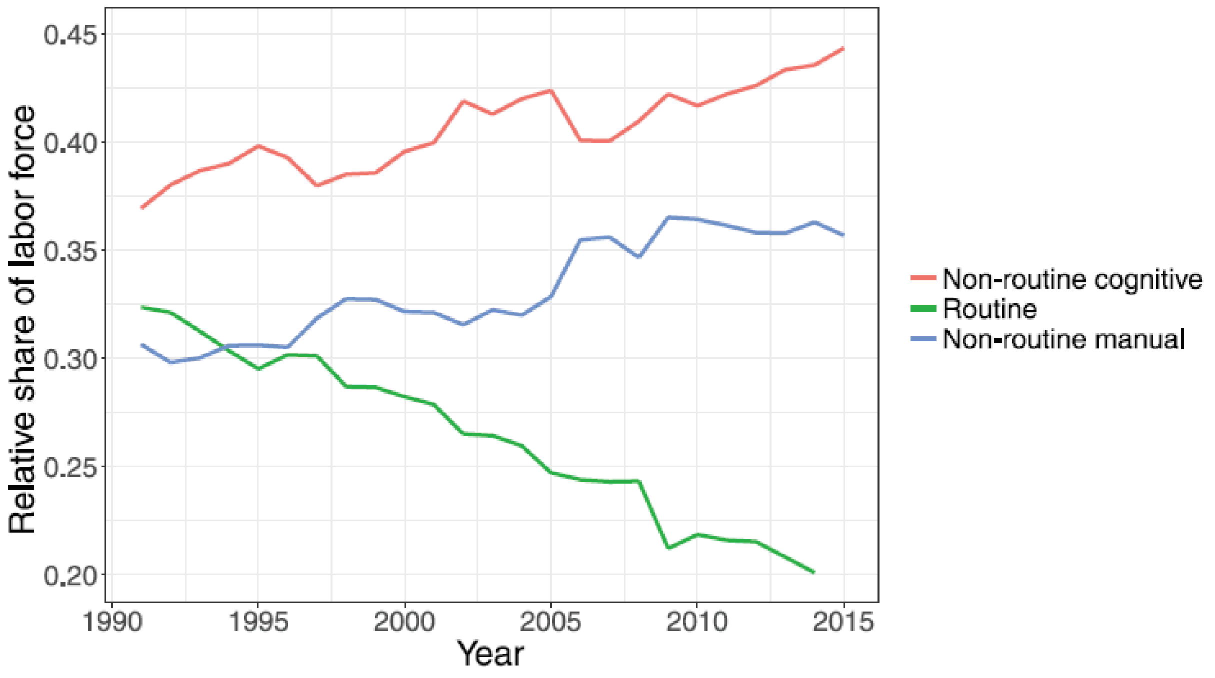
uc3m | Universidad Carlos III de Madrid

14%

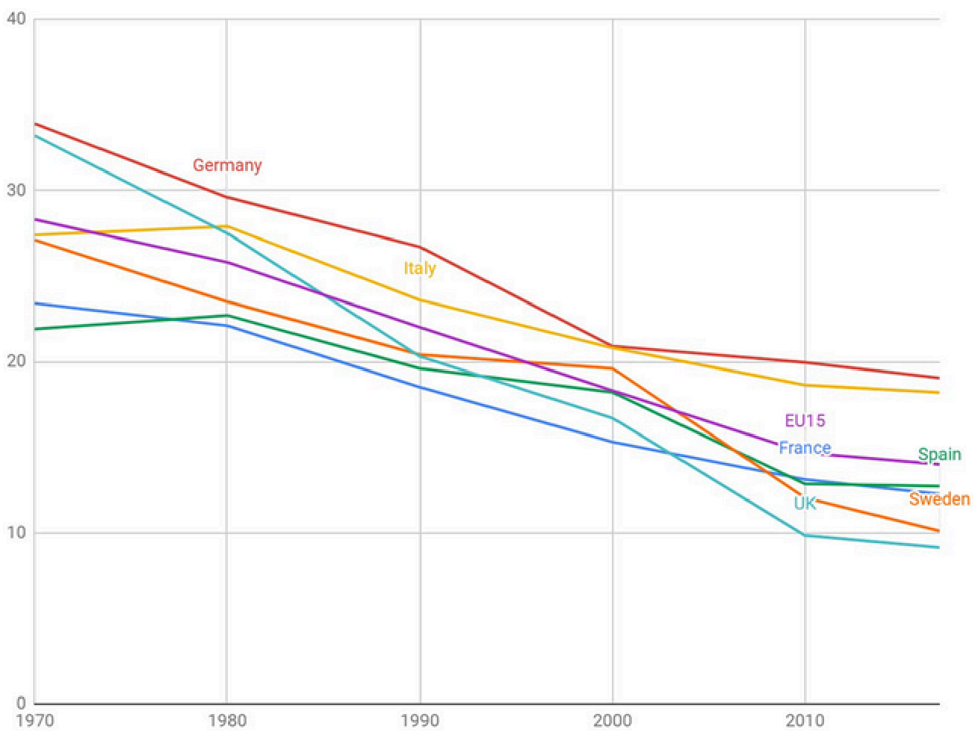
OF THE GLOBAL WORKFORCE

The McKinsey Global Institute estimates that up to 375 million workers globally may need to transition to new occupational categories due to rapid automation adoption (2017) .

Introduction and literature review



Aggregate trends in the employment structure (1990–2015).
Source: Gallego, A. & Kurer, T. (2019). Distributional consequences of technological change: Worker-level evidence. Research & Politics, 6(1), 2053168018822142.



Share of employment in manufacturing in Europe (1970–2016).
Source: Klenert, D., Fernandez-Macias, E., & Antón, J. I. (2023). Do robots really destroy jobs? Evidence from Europe. Economic and Industrial Democracy, 44(1), 280-316.

"There are still many areas, particularly those requiring complex problem-solving and human interaction, where machines cannot yet replace humans" **(Chui et al., 2016).**

Following Georgieff and Hyee (2021), it is useful to think of AI-driven automation as having two possible, but opposite, **effects on employment:**
I. On the one hand, AI can reduce employment through **automation/substitution**.
II. On the other hand, it can boost employment by increasing **worker productivity.**

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, the main purpose is to investigate whether:
I. **Low-skilled** manual occuaptions are experiencing job losses, perhaps due to automation.
II. **High-skilled** occupations benefit from technological progress in terms of employment.

How? Data & Pre-processing

European Commission
JOINT RESEARCH CENTRE

eurostat

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

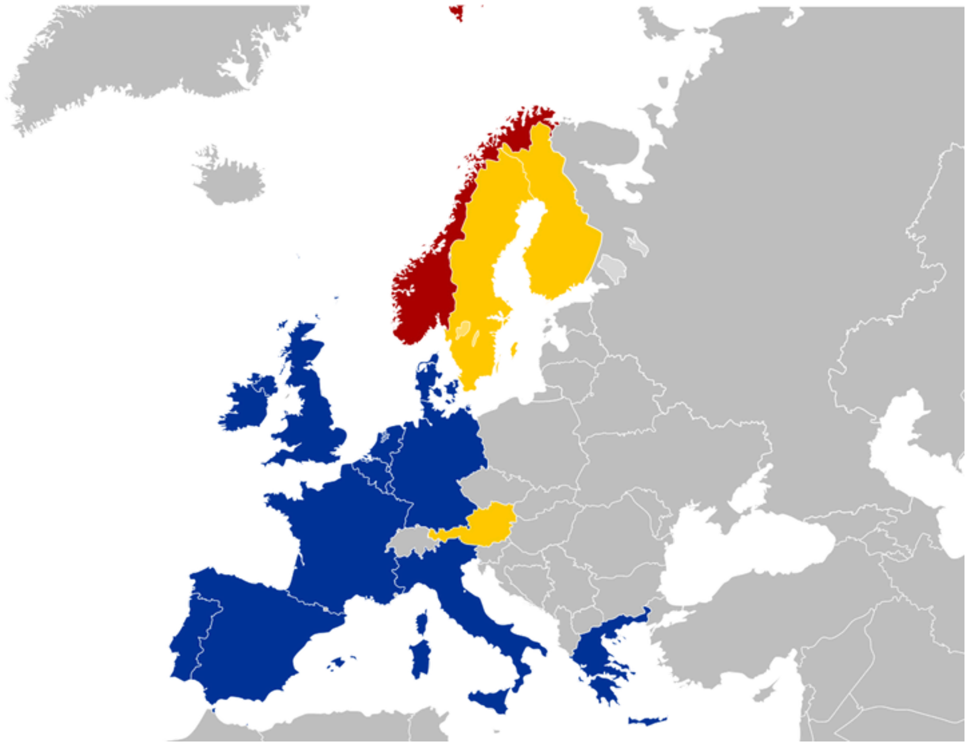
In terms of the methods
Autonomy
Teamwork
Routine

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
Ratio of female participation

The **EU Labour Force Survey (EU-LFS)**, is a large household sample survey providing quarterly and yearly results on labor participation of people inside and outside the labor force. The **European Database of Task Indices** 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.



The whole **EU15** (minus the UK), i.e., Austria, Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, The Netherlands, Norway, Portugal, and Sweden.

from **2012 to 2021**

The **2-digit ISCO-08** version was employed, which covers a total of **40 occupations.**

Occupations and employment in Europe: Descriptive results

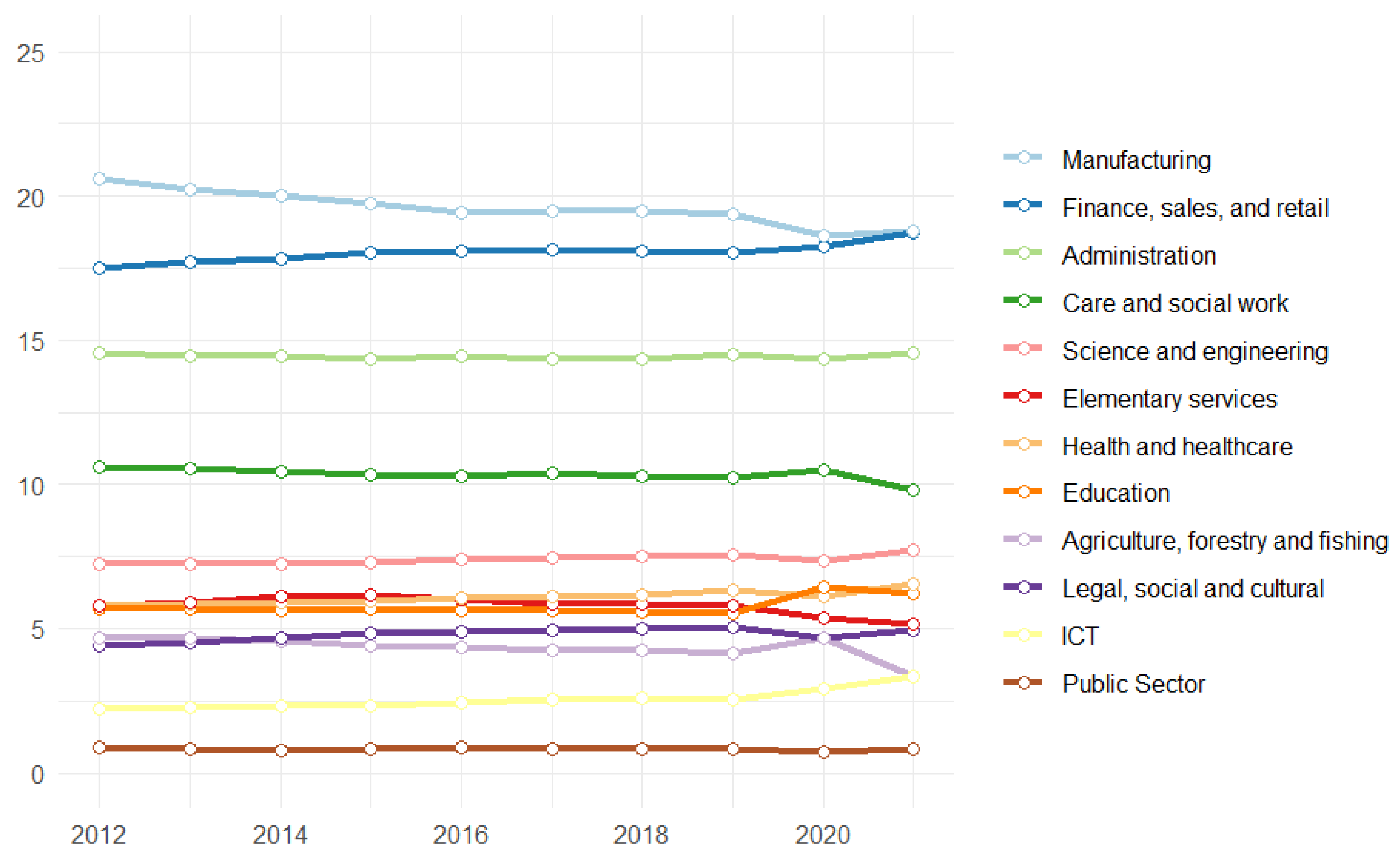


Figure 1. Yearly evolution of the employment share by sector (2012-2021).
Source: own elaboration with data from the Labor Force Survey

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

Figure 2. Taxonomy of tasks across sectors of activity.
Source: own elaboration with data from the Joint Research Center.

Occupations and employment in Europe: Descriptive results

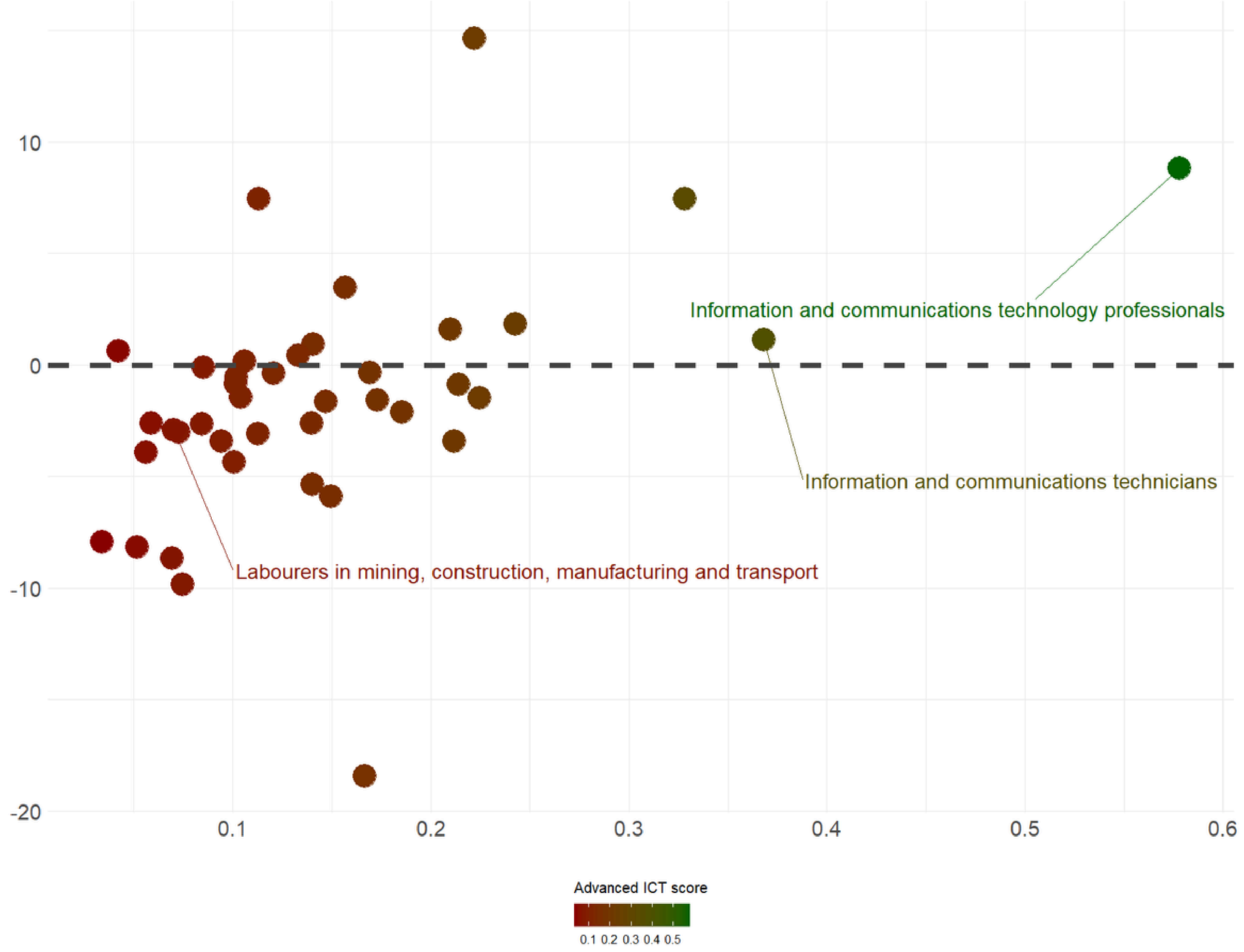


Figure 3. Use of Advanced ICT and employment rate variation across occupations (2012-2021)
Source: own elaboration with data from LFS and JRC.

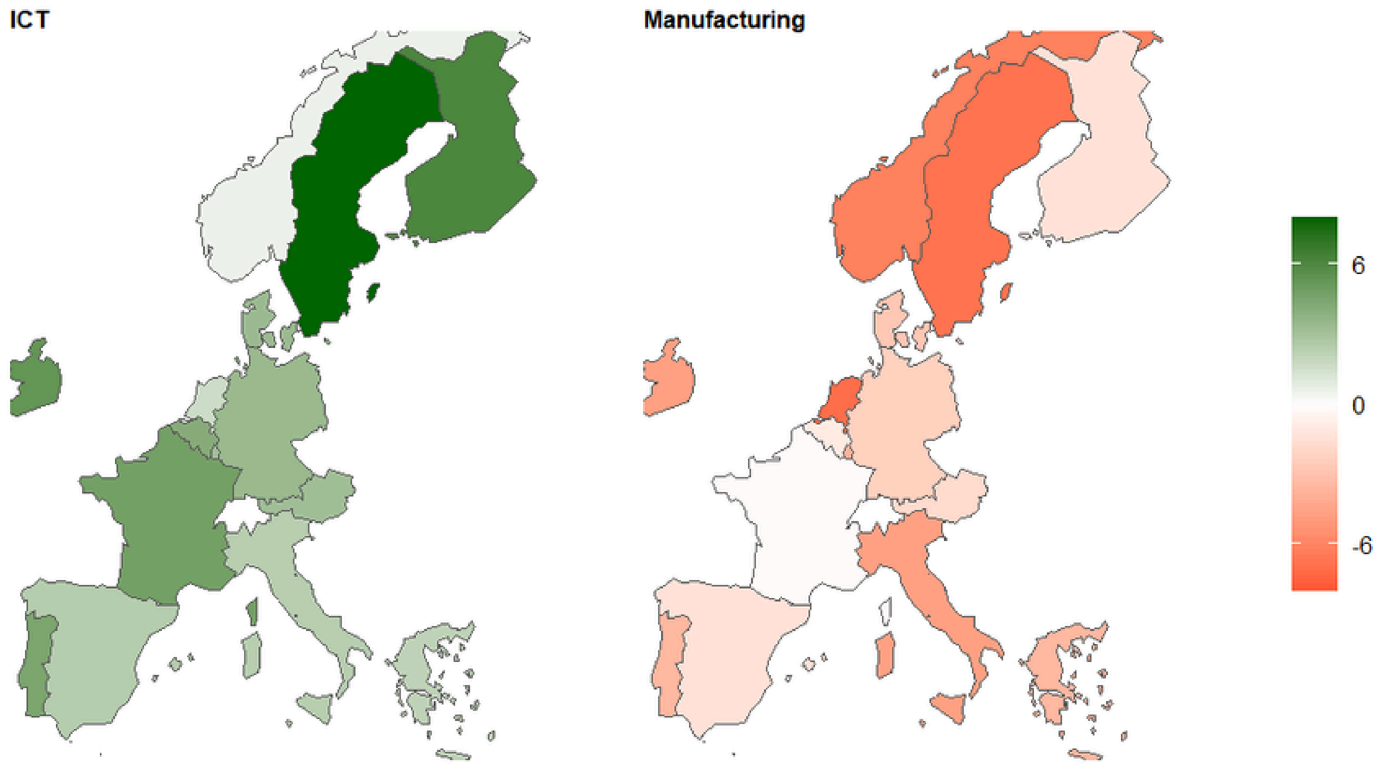


Figure 4. Cross-country differences in employment rate variation between ICT professionals and manufacturing industry (2012-2021).
Source: own elaboration with data from LFS.

As observed in **Figure 3**, employment increased in the most ICT-intensive occupations between 2012 and 2021, and decreased in the manufacturing sector.
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.

Occupations and employment in Europe: Methodology

Defining the **target variable:** Employment variation

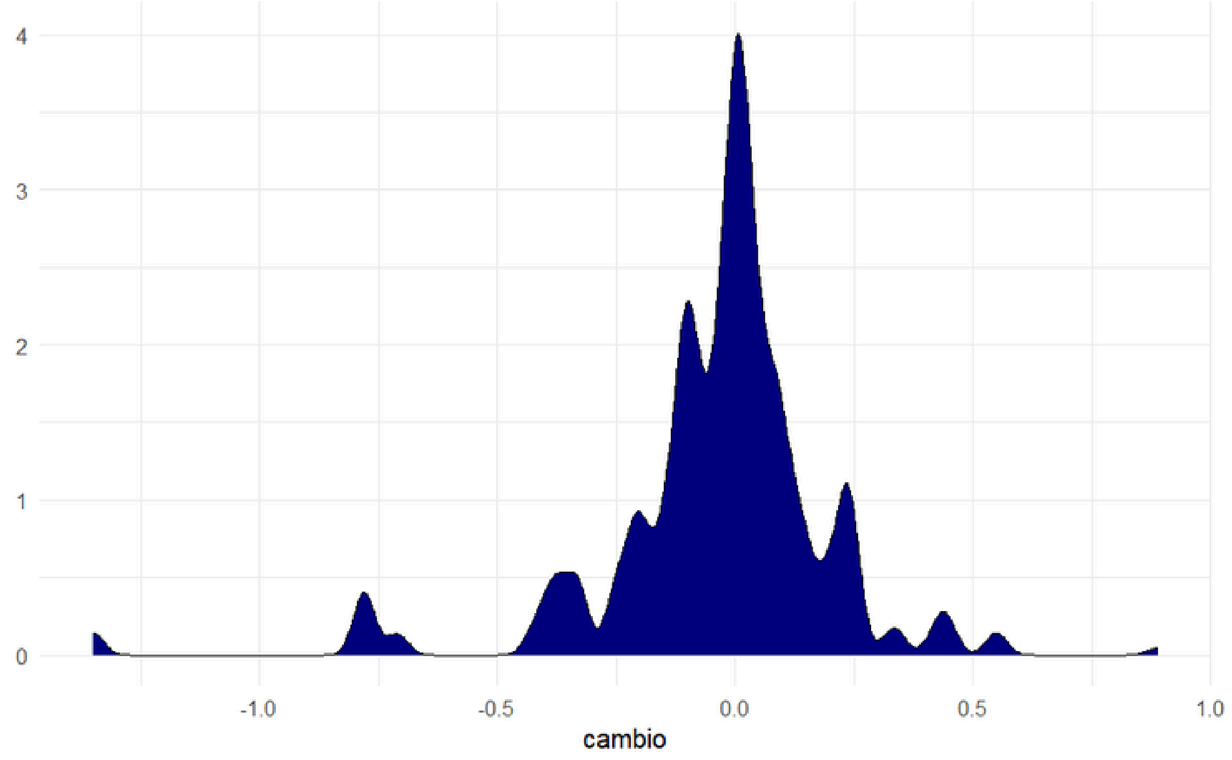
Measuring employment and unemployment

Should statistical criteria for measuring employment and unemployment be re-examined?

Source: Brandolini, A., Viviano, E. (2018). Measuring employment and unemployment. IZA World of Labor 2018: 445 doi: 10.15185/izawol.445

"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."*

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.**



YEAR	sector	share	cambio
2012	Administration	14.56911	0.00
2013	Administration	14.47307	-0.10
2014	Administration	14.45033	-0.02
2015	Administration	14.35633	-0.09
2016	Administration	14.44765	0.09
2017	Administration	14.34586	-0.10
2018	Administration	14.35752	0.01

Occupations and employment in Europe: Methodology

Regression method: Linear Mixed Effects Models

Linear mixed models (LMM), also known as **multilevel**, 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 **hierarchical** data structures.

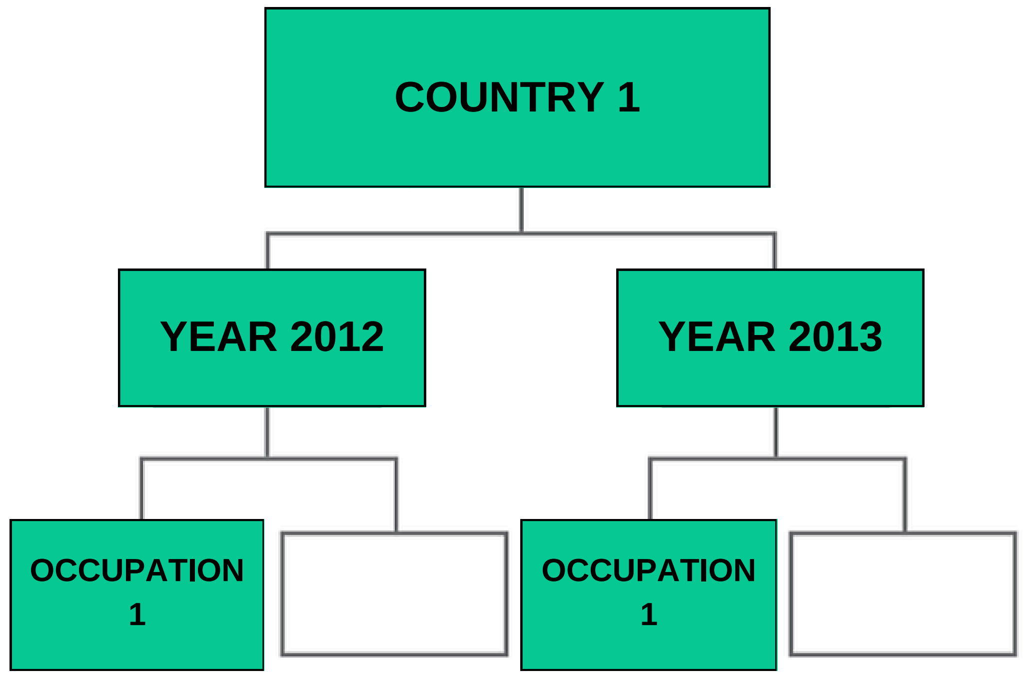
- ***Fixed effects*** provide a way to account for specific variables that remain constant across observations. This is the case of our predictors from the JRC, which are constant across countries and years.

- ***Random effects*** account for the variability between distinct entities within the larger group. The unique variations at each level of our data hierarchy can be modeled.This is the case of our predictors from EU-LFS.

Lasso Regression

glmnet

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.



Results and Discussion

	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)

Table 2. Estimates of the independent variables on the employment share variation.

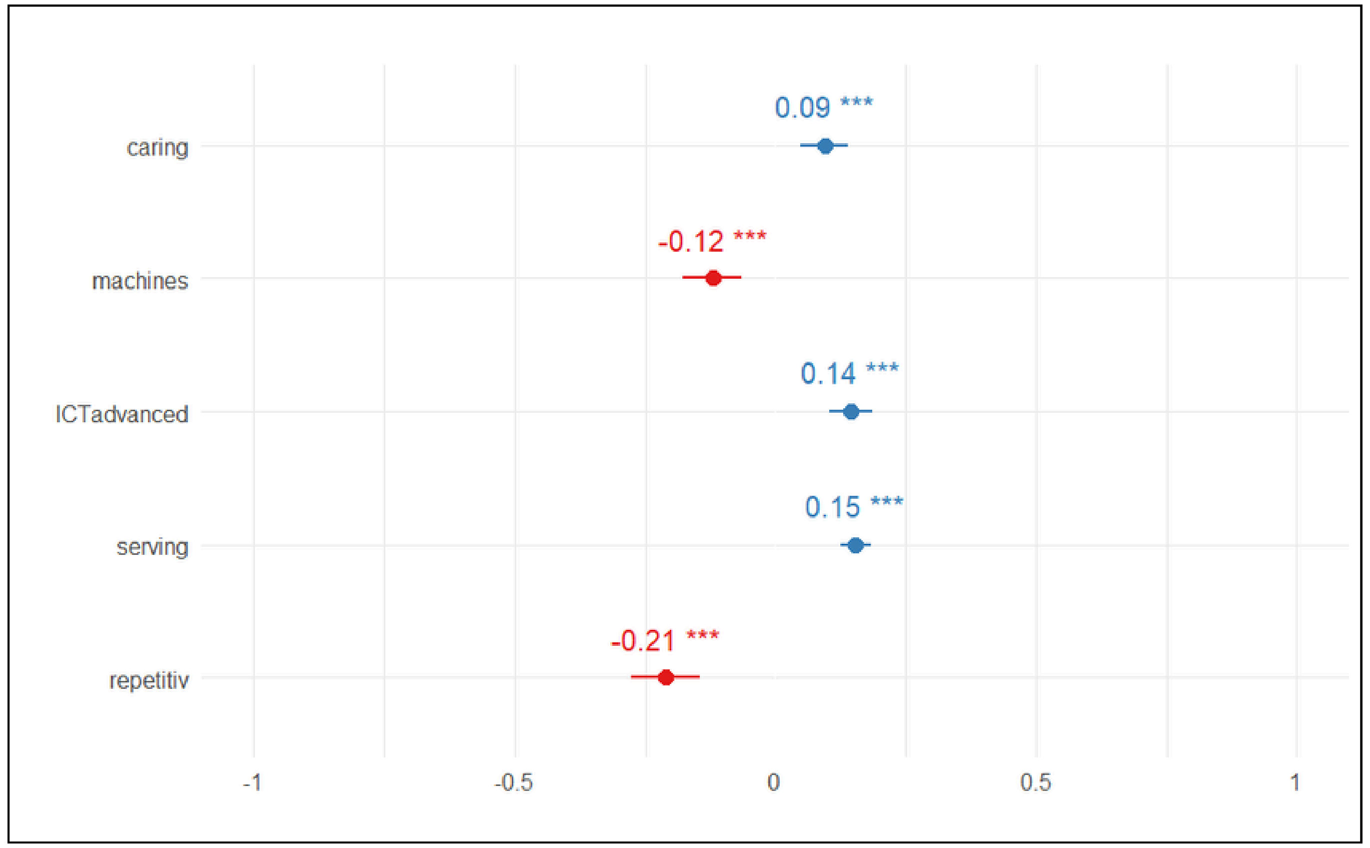


Figure 5. Fixed effects of the Linear Mixed Model (2).

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 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.

Conclusions and Limitations

Conclusions:

- The use of 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.

Limitations:

- 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.
- The **lack of variability** of the JRC predictors, assuming that these predictors apply consistently across different regions and time periods, which could potentially oversimplify the impact of occupational characteristics on employment trends.

Further research:

- Building a predictive model to forecast the employment evolution of occupations based on their occupational characteristics.
- Studying employment trajectories on exclusive levels of the occupational structure, i.e., low-skilled vs high-skilled sector.
- Female occupational trajectories in increasingly automated and digitalized labor markets differ systematically from male trajectories.

THANK YOU!

uc3m | Universidad Carlos III de Madrid

References

Acemoglu, D., & Autor, D. (2010). Skills, Tasks and Technologies: Implications for Employment and Earnings. National Bureau of Economic Research.

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in US wage inequality. Econometrica, 90(5), 1973-2016.

Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris, https://doi.org/10.1787/5jlz9h56dvq7-en.

Autor, DH., Levy F., & Murnane, RJ. (2003). The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118(4):1279–333.

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2021). New frontiers: The origins and content of new work, 1940–2018. The Quarterly Journal of Economics.

Autor, D. (2022). The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty (No. w30074). National Bureau of Economic Research.

Bisello, M., Fana, M., Fernandez Macias, E. and Torrejon Perez, S., A comprehensive European database of tasks indices for socio-economic research, European Commission, 2021, JRC124124.

Brandolini, A., Viviano, E. (2018). Measuring employment and unemployment. IZA World of Labor 2018: 445 doi: 10.15185/izawol.445

European Commission. (2009). Commission Recommendation on the use of the International Standard Classification of Occupations (ISCO-08).

Gallego, A. & Kurer, T. (2019). Distributional consequences of technological change: Worker-level evidence. Research & Politics, 6(1), 2053168018822142.

Gallego, A., & Kurer, T. (2022). Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior. Annual Review of Political Science, 25, 463-484.

Georgieff, A. and Hyee, R. (2021), "Artificial intelligence and employment: New cross-country evidence", OECD Social, Employment and Migration Working Papers, No. 265, OECD Publishing, Paris, https://doi.org/10.1787/c2c1d276-en.

Klenert, D., Fernandez-Macias, E., & Antón, J. I. (2023). Do robots really destroy jobs? Evidence from Europe. Economic and Industrial Democracy, 44(1), 280-316.

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., ... & Sanghvi, S. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute, 150(1), 1-148.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). A future that works: AI, automation, employment, and productivity. McKinsey Global Institute Research, Tech. Rep, 60, 1-135.

Oesch, D. (2006). Coming to Grips with a Changing Class Structure: An Analysis of Employment Stratification in Britain, Germany, Sweden and Switzerland. International Sociology, 21(2), 263-288. https://doi.org/10.1177/0268580906061379

Schumpeter, J.A. (1950) The Process of Creative Destruction. In: Capitalism, Socialism and Democracy, 3rd Edition, Allen and Unwin, London.

Silva, H. C., & Lima, F. (2017). Technology, employment and skills: A look into job duration. Research Policy, 46(8), 1519-1530.

Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. (2018). The impact of automation on employment: just the usual structural change?. Sustainability, 10(5), 1661.