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The Impact of Occupational Exposure to Artificial Intelligence: Early Evidence from Europe

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Thesis Title:
The Impact of Occupational Exposure to Artificial Intelligence: Early Evidence from Europe.

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Abstract: This thesis investigates the impact of occupational exposure to artificial intelligence (AI) on employment in the EU15 countries from 2015 to 2019. I use a cross-section regression where the dependent variable represents a value-change in a employment share regressed against a non-time variant occupation-level AI exposure measure, along with relevant controls. Specifically, amongst other factors, the analysis controls for occupational routine and offshorability. The thesis contributes the literature by utilizing a more modern method of translating US measures on the impact of AI for use in the European context. Key findings indicate that AI exposure increases employment shares, thus particularly enhancing some high-skill occupations which have a greater AI exposure. The study also examines the role of institutional complementarities through proxies for innovation and political economy types, findings indicate that, unlike previous waves of employment automation, AI is not as dependent on national institutional complementarities, with a slight negative correlation to innovative ecosystems. Finally, this thesis also contributes to the literature by linking AI impacts with previous literature on technological advancements. The findings provide valuable insights for policymakers to maximize AI's benefits without unfounded concerns for negative employment effects.

Key Words:
Artificial Intelligence (AI), Occupations, Employment, Labour Markets, Europe.

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1. Introduction

“A workman … not acquainted with the use of the machinery employed ... could scarce, perhaps, with his utmost industry, make one pin in a day, and certainly could not make twenty” – Adam Smith, 1776.

The interplay between technological automation and work has captivated the minds of social science scholars and especially economists for centuries (Smith, 1776; Keynes, 1930). Recent advancements in the field of machine learning and today’s omnipotent generative artificial intelligence programs like ChatGPT, have renewed academic interest and efforts to study the ongoing and expected effect that such new technologies will have on employment.

This thesis is part of these academic efforts, contributing to a better understanding of the impact that the increasing use and capabilities of Artificial Intelligence (AI) have had on employment.

1.1 Topic and Research Question

I examine this impact on the so called EU15 group of European countries during the period 2015-2019, when advanced AI techniques like machine vision and deep learning where entrenched in various work tools and processes (LeChun et. al, 2015)[1]. The timing of these advancements was the result of 21st century progresses in computing power, modeling and the vast data availability created by the expansion of the internet.

The research question of the thesis is: ‘How has the occupational exposure to Artificial

[1] The EU15 group of countries refers to the first 15 members of the European Union, it comprises of: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

Intelligence (AI) affected employment shares in European counties between 2015 and 2019, given institutional complementarity differences?'. To answer this question, I have conducted an OLS cross-section regression analysis to measure how different occupations in different European countries have been affected by AI. To do so, I have regressed the relative change in employment share of different occupational categories (during the 2015-2019 period), against a measure of exposure to AI for each category, including controls for occupation-specific, worker-specific and country-specific characteristics.

1.2 Contributions

My contribution to the literature is threefold.

Firstly, at the time of writing, my thesis contains the first empirical test in the literature on AI employment automation in Europe that includes controls for occupational routine. By doing so, this thesis enables comparisons between developments and academic findings regarding technological automation in employment during the 1990's and 00's with subsequent technological automation in employment linked to AI, thus connecting the literatures around the so-called 3^{rd} and 4^{th} industrial revolutions. Moreover, unlike the routine measure of the aforementioned studies, which largely adapt occupational routine measurements from the US O*NET's Standard Occupational Classification system (O*NET, 2024), this is also the first time that the measure of routine used in the AI employment literature is based on European data and thus European classifications. More specifically, I use data from the 'European Database of Tasks Indices for Socio-Economic Research' (Bisselo et. al, 2021), a joint project between the European Commission and Eurofound that assigns scores for a variety of task content and task content categories to each 2-digit occupational category of the International Standard Classification of Occupations (ISCO, ILO, 2024). Relevant data for the routine related measurement originated from the 2015 European Working Conditions Survey (EWCS, 2015). This means that this thesis is testing actual reported routine by European workers against the employment shares of their occupations instead of adapting estimated routine levels from US data.

The second and more significant contribution of my thesis is that, at the time of writing, it is the first study that tests for the role that international variations in institutional complementarities, such as innovation and political economy, have had in terms of how AI has impacted employment.[2] The role of institutions is well entrenched in labour economics in general, but also studies of technological automation and work in particular. I test for such variations by including proxies of different levels of innovation per country, groupings of European counties according to the political economy-type of their institutional complementarities, as well as through generic country dummies. By including these controls in my analysis I have contributed both to a better understanding of how AI has affected occupations in Europe and I have also linked this emergent literature with the well-established insights of the institutional and labour automation literatures.

Finally, this thesis is the first study of the impact of AI occupational exposure on employment in Europe, that uses the more precise AI-based O*NET-to-ESCO crosswalks for translating data from US occupational classifications to European occupational Classifications.

1.3 Thesis Structure

The rest of this thesis will be structured as follows: the next chapter is the literature review, where I will outline the literature on technological automation and employment following its

[2] The term 'Institutional Complementarities' is used primarily in political economy literature to refer to the systemic effects and characteristics created by the interactions between different national institutions, be it public or private, economic or political, or otherwise.

course and content up to the current studies on the impact of AI on occupations. Following the literature review I will present the theoretical and operational framework of the thesis, defining the key concepts. I will then devote a chapter on data, including the main data sources I use, the limitations of these data, how I have structured them for my analysis and the methods I have used to construct the variables of the regression. The fifth and last chapter is devoted to the empirical analysis of the thesis, it includes descriptive statistics for variables, a presentation of the empirical strategy (specifically a phased description of the type and structure of the regression), a presentation of the relevant results and their interpretation and finishing with a discussion on possible real-world and policy implications. The thesis ends with some concluding remarks.

2. Literature Review

2.1 Overview of the literature on Technological Automation and Employment (up to AI)

The relationship between technology and work has been a central theme in the study of economic discourse since its inception. In this first part of my literature revie I make a quick reference to the evolution of the literature on labor automation, setting the stage for the contemporary literature on the impact of artificial intelligence.

According to research by Acemoglu, Johnson, and Robinson (2005), the emergence of the 1st industrial revolution, a significant turning point in economic history and the first major labour automation phase, was the result profound institutional changes that catalyzed economic growth and technological advancements (Stasavage, 2003). This period spanned the 19th century, and was characterized by technologies such as mechanization and steam power, which fundamentally transformed the nature of work and employment.

Subsequently, there was the 2nd Industrial Revolution, characterized by mass production and electrification, commencing by such changes as the Ford Motor Company's pioneering assembly line in the late 19th century and lasting until around 1980. It was during this period that economists began to consciously realize the impacts of automation technologies on the labor market. See for example Keynes' essay on 'Economic Possibilities for our Grandchildren' (Essay in Persuasion, 2010 [1930]) and works by Nobel laureate Wasilly Leontief (Leontief, 1952, 1983; Leontief & Duchin, 1986). At the same time economists also begun to understand the so called "Luddite Fallacy"— i.e. the mistaken belief that technological innovation will have a long-lasting detrimental effect on employment (Demetriou, 2022).

Though the technological unemployment fears of these periods did not materialize in the long term, starting from the 1980s the workers did see their share of national income falling, and most developed economies experienced a significant increase in income inequality (World Bank Data for the US, 2022). Many middle-class workers have been relegated to more precarious, lower-paying jobs (Pariboni and Tridico, 2019; Case and Deaton, 2020). Research in the field has shown that technological innovations since the 1980s have been a main culprit for these increase job precariousness, pushing workers into lower-skill professions (Autor, Dorn, & Hanson; 2015, 2016). The technologies driving these changes were collectively described as the "3rd industrial revolution" or the "digital revolution," characterized by the shifts from mechanical and analog devices to digital electronics and automation, alongside the proliferation of information and communication technologies.

2.2 Technological Automation and the Role of Routine and Offshoring

It's also during this period that more sophisticated schools of thought were created around how exactly technological automation has affected employment through the years. The first major school of thought on the topic focused skills, arguing that the effect mechanism of technological automation is primarily skills-based (Goldin and Katz, 2008; Autor D. & Katz 1999; Autor D. 2014, 2017). The idea being that skills of workers are rendered obsolete faster than they can be reskilled, as a result leading to technological unemployment. A later and (in my opinion) more sophisticated school of thought focused on the tasks instead of the skill composition of jobs, arguing that it's tasks really that become obsolete, not skills and certainly not occupations. In particular, empirical evidence suggested that routine tasks tended to be the most vulnerable to automation, creating the so called "routine-biased" approach to employment changes due to technology (Goos et. al, 2014).

At the same time as arguments were put forward about the role of work-routine in job automation, the acceleration of globalization and liberalization of international trade in the early 1990s prompted scholarly attention towards offshoring of jobs from developed to developing economies as another contributing factor to the negative changes in employment during this period. Many empirical studies have created and refined an "offshorability" variable to capture this effect on employment (Firpo et. al, 2011; Autor D., 2013, 2016; Blinder and Krueger, 2013). Nevertheless, notable empirical works have argued that the effects of the offshoring of jobs was at best secondary to that of technology (Goos et. al, 2014; Hummels et. al, 2018).

Some of the empirical results of the most high-profile papers on these effects confirm that the so called 'Routine-biased technological change' (RBTC) and offshorability have had empirically significant impacts on employment during the "3rd industrial revolution' period (~1980-2010). Autor, Levy, and Murnane (2003) provide regression results indicating that between 1970 and 1998, a 10% increase in computer usage within an industry correlates with a 4.2% decline in routine task employment (p. 1301). Autor and Dorn (2013) show that from 1980 to 2005, a one standard deviation increase in the share of routine jobs results in a 0.2 percentage point annual decline in routine jobs (pp. 1568-1572). Goos, Manning, and Salomons (2014) find that between 1993 and 2010, RBTC accounts for a significant portion of within-industry employment shifts, with routine occupations declining by 1.5% per decade, while non-routine cognitive and manual tasks increased (p. 2517). Acemoglu and Autor (2011) document that from 1980 to 2005, a one standard deviation increase in technology adoption leads to a 0.25 percentage point annual decrease in routine employment (p. 1060). Regarding offshorability, Goos, Manning, and Salomons (2014) show that between 1993 and 2010, occupations with high offshorability experience a 0.5% annual decline in employment (p. 2518). Additionally, Hummels et al. (2014) find that from 1995 to 2006, offshoring leads to a 3.3% wage decline in routine jobs (p. 1603). These results collectively highlight the substantial impact of RBTC on reducing routine task employment over multiple decades, while the effect of offshorability, although present, is quantitatively smaller but still significant in shaping labor market dynamics.

2.3 The Arrival of AI and Employment

From roughly 2010 onwards AI advancements started to become more sophisticated, in turn leading to gradual adoption in workplaces in various industries. Advancements in AI techniques like machine vision, language and speech recognition and deep learning where entrenched in various work tools and processes (LeChun et. al, 2015; Felten et. al, 2019).

A seminal bridging study in the relevant literature was that of Frey and Osborne (2017), who demonstrated that a significant portion of jobs, particularly those involving routine tasks, are at high risk of automation from AI and other ICT advancements (Frey and Osborne, 2017). They estimated that approximately 47% of total US employment could be automated, emphasizing the vulnerability of routine-based occupations. Brynjolfsson, Rock, and Syverson (2017) extended this analysis by examining the suitability of various tasks for machine learning (ML). Their findings indicate that while most occupations have tasks suitable for ML, few jobs can be fully automated, suggesting that job redesign, rather than wholesale job replacement, will be more prevalent (Brynjolfsson et al., 2017).

The relationship between AI and wage inequality is another critical area of investigation in the literature. Webb (2020) used natural language processing (NLP) to link patent texts to occupational tasks, finding that AI predominantly targets high-skill tasks, potentially reducing wage inequality between high and low earners but not affecting the top 1% of earners (Webb, 2020). This contrasts with earlier technologies, which primarily automated lower and middle-skill tasks, exacerbating wage disparities. Felten, Raj and Seamans (2019) focused on the heterogeneous impacts of AI on wages. They found that occupations requiring higher levels of software skills tend to benefit more from AI advancements, suggesting that the wage impacts of AI are uneven across different skill levels and industries (Felten et al., 2019). Albanesi et al. (2023) provided a comparative analysis of AI's impact on employment in Europe. Their findings indicate significant variation in how different European labor markets experience AI-induced employment changes, reinforcing the importance of context-specific policy interventions (Albanesi et al., 2023).

2.3.1 AI Measurement methodologies in the literature

The academic literature on measuring the impact of AI on employment uses various methodologies which can be I broadly separated into to task-based approaches and demand-based approaches.

Starting from the task-based approaches, notable methods include the Suitability for Machine Learning (SML) rubric developed by Brynjolfsson, Mitchell, and Rock (2018), which evaluates tasks based on their suitability for machine learning by considering factors like data availability and performance metrics clarity (Brynjolfsson et al., 2018). Another significant method is the AI Occupational Exposure (AIOE) measure by Felten, Raj, and Seamans (2018), which links AI capabilities to occupational abilities using the O*NET database and evaluates the exposure of occupations to AI based on the importance and prevalence of specific abilities required in those occupations (Felten et al., 2021).

On the demand-based approaches, an often cited approach is that of Webb (2020) who specifically introduces a patent-based approach, measuring the overlap between AI-related patents and job descriptions to gauge the potential for task automation, highlighting the exposure of tasks to AI by examining patent claims and job descriptions (Webb, 2020, p. 4). Alekseeva et al. (2021) use data from the Burning Glass institute[3], quantifying the incidence of AI-related skills in job postings to track shifts in demand and correlate these with wage changes. (Alekseeva et al., 2022) . Acemoglu et al. (2022) use more of a hybrid approach, they first use the AI occupational exposure measure of Felten et. al (2021) to inform the kind of demand they are looking for and then use data from Burning Glass Institute to monitor the evolution of AI skill demands in job postings, providing a direct indicator of how industries and occupations are adapting to AI integration. The demand-approach papers based on the Burning glass data method show a significant increase in AI-related job postings over time,

[3] The Burning Glass Institute is an organization focused on researching the evolving job market and workforce. It works with educational institutions, businesses, and policymakers.

serving as a proxy for AI adoption in various sectors

These methodologies offer diverse perspectives on assessing AI's potential impact on labor markets, from task suitability and patent overlaps to detailed occupation-level exposure and demand-based assessments. I have chosen to use a task-based approach, a choice that I will analyze in the next chapter.

2.3.2 Regressions approaches and results

The regression approaches used across the literature to measure the impact of AI on employment incorporate various econometric techniques, each with distinct regression types and a range of control variables.

Webb (2020) employs a panel data regression with industry fixed effects model to isolate within-industry changes in occupation demand and wages for the period 2007- 2016, controlling for exposure scores transformed into employment-weighted percentiles. His analysis is for the US. The control variables include the degree of automation, the importance of programming at the occupation level from ONET data, offshorability measures, occupational licensing, and various census variables such as age, gender, and education level. (Webb, 2020, pp. 1-12, 22-23, 56). Though Webb also compares his results to routine measures used in the past literature he does not control for any national institutional factors (Webb, 2020, pp. 57-60). He finds that AI exposure correlates with a 4% decrease in 90:10 wage inequality but a marginal increase in 99:90 inequality, suggesting wage compression in the middle and expansion at the top, implying that AI's impact is more significant in higher-wage occupations (p. 43-44).

Albanesi et al. (2023) utilize a cross-section regression model with sector-occupation fixed effects, including measures of exposure to AI and software. Their investigation spans different Euroepan countries. The dependent variables they use are changes in employment shares and wage distributions during the period 2011-2019. The control variables encompass sector clustering, sector and country dummies, and average wages. They do not control for routine or affordability directly, nor for any national institutional factors (Albanesi et al., 2023, pp. 15-18). The find that AI-enabled automation correlates with employment increases in high-skill occupations. However, the relationship between AI exposure and wages is generally negative and insignificant. Specifically, the regression analysis in the paper shows that AI-enabled automation is positively associated with employment shares, with Webb's AI exposure measure indicating a 2.6% increase and Felten et al.'s measure a 4.3% increase when moving from the 25th to the 50th percentile of AI exposure. However, AI exposure does not significantly impact relative wages. These results suggest that AI-related displacement effects are minimal. ountries with higher Digital Economy and Society Index (DESI) scores, such as Finland, the Netherlands, and Austria, experience more substantial positive impacts from AI-enabled automation due to faster technology adoption and better digital infrastructure. In contrast, countries with lower DESI scores, like Greece, Italy, and Latvia, show lesser positive impacts or even neutral effects due to slower technology adoption (pp. 23-24). Structural features also play a critical role in these variations. Countries with higher product market regulation and stricter employment protection legislation, such as Greece and Lithuania, show lower positive impacts of AI on employment. Such regulations seem to impede the adoption and diffusion of AI technologies. Conversely, countries with lower regulatory barriers and more flexible labor markets, like Germany and Finland, exhibit positive associations between AI exposure and both employment shares and relative wages, indicating a complementary relationship (Albanesi et. al, 2023, pp. 46-47). Furthermore, higher scores in governance and educational attainment correlate with more significant positive employment effects from AI, suggesting that robust governance and a skilled workforce facilitate the integration of AI technologies into the labor market (Albanesi et. al, 2023, pp. 23-24).

Acemoglu et al. (2021) use a cross-section regression approach at the establishment level, including controls such as industry dummies, firm size deciles, commuting zone dummies, and firm fixed effects. Their investigation is US focused. The dependent variables are changes in job posting outcomes, vacancy flows, non-AI hirings, and job skill requirements from 2010 to 2018. They do not control for routine or offshorability directly, nor for any national institutional factors (Acemoglu et al., 2021, pp. 1, 11-12, 14). The paper finds that a 1 standard deviation increase in AI exposure results in a 7.2% decline in non-AI employment between 2010 and 2018. Furthermore, a 1 standard deviation increase in AI exposure is linked to a 14% decrease in non-AI vacancies (pp. S308-S310, S326-S327).

The paper by Alekseeva et al. (2021) uses ordinary least squares (OLS) regressions to analyze the impact of AI on wages across various industries and occupations. Their analysis is US focused. The primary dependent variable in these regressions is the log of wages, with the time period for data collection spanning from 2016 to 2019. The main independent variable is a dummy indicating the presence of AI-related skills in job postings. The study includes a range of control variables, such as other skill requirements (e.g. Software, Cognitive, Social, Character), firm-level characteristics (e.g. market capitalization, employment, sales, market-to-book ratio), as well as fixed effects for time, industry, labor market, firm, and job title. They An AI skill requirement raises wages by 16%, and when controlling for firm fixed effects, the premium is 20%. Additional controls reduce the premium to 11% and 5%, indicating a robust impact of AI on wages (pp. 14-16).

Georgieff and Hyee (2021) apply a cross section regression approach, incorporating country fixed effects and robust standard errors looking at different OECD countries. The dependent variable is employment growth across occupations and countries. Their model includes controls for the share of tradable sectors, offshorability, exposure to software and robots, and one-digit occupational ISCO dummies. (Georgieff & Hyee, 2021, pp. 36-38). Though they take routine in consideration for their conceptual framework they do not control for it in their regression. The impact on overall employment levels is mixed, varying significantly across sectors and occupations. The paper reports that AI exposure leads to a decrease in average weekly working hours, especially in occupations with low computer use. Specifically, a one standard deviation increase in AI exposure is linked to a 0.60 percentage point drop in weekly working hours (about 13 minutes) in low computer use occupations. Additionally, AI exposure increases the share of part-time employment in these occupations

Felten, Seamans, and Raj (2019) use cross-section regression with US state-level fixed effects to analyze the relationship between AI impact and wages and labor in the US, they do so by using employment and wage data from the Bureau of Labor Statistics for each occupation from 2010 to 2016. Their models also controls for laws, regulations and other occupational characteristics using O*NET and Burning Glass data, specifically including the degree of automation and importance of programming, but do not include offshorablity or routine (Raj, Seamans, and Felten, 2019, pp. 4, 13, 20-22). Their results that AI has a significant positive effect on wage growth but not on employment growth. A one standard deviation increase in the AI Occupational Impact (AIOI) score is associated with a 0.41 percentage point increase in wage growth. For high-software-prevalence occupations, this increase is 0.61 percentage points. However, no significant relationship exists between AIOI and employment growth.

The empirical model of this thesis follows the approach used by these papers i.e. a cross-section regression where the dependent variable represents a value-change for a specific period regressed against a non-time variant occupation-level AI measure along with controls. Regression form followed by most papers in the literature is approximately:

$$\Delta Y_{o,1\ and/or\ 2} = \beta_0 + \beta_1 AI_{o\ or\ o,1} + \gamma_1 X_{o,1\ and/or\ ,2} + \alpha_1 + \alpha_2 + \varepsilon_{o,1\ and/or\ 2} \qquad (1)$$

(where Δ may represent a difference or relative change or percentage change etc., 'o' represents occupations (or occupational categories), and 1, 2 indicate a geography-area or an industry and in the case of Webb 2020 both these two and also time)

More specifically I follow the regression approach by Felten et. al with consideration for the approach of Georgieff and Hyee as well as Albanesi et. al. However, I focus on EU countries (the EU15 group) not US states or the OECD members. In addition, unlike the papers that cover Europe (Georgieff and Hyee and Albanesi et. al), I explicitly include a control for occupational routine in my empirical model, this is my secondary contribution to the literature as no other paper on Europe has included such a control up to the time of writing.

2.3.3 Findings on the Role of National Institutional Factors

The literature also investigates how the impact of AI on labor markets is shaped by national institutional factors. Research by Albanesi et al. (2023) and Georgieff & Hyee (2021) offers insights into how these elements influence the integration and effects of AI technologies within different national contexts.

First, the degree of digital infrastructure, as measured by the Digital Economy and Society Index (DESI), is a critical determinant. Nations with advanced digital infrastructures, such as Finland, the Netherlands, and Austria, show a strong positive correlation between AI exposure and employment growth. In these countries, occupations that heavily utilize digital technologies and AI not only retain but also expand their workforce, suggesting that robust digital infrastructure facilitates effective AI integration and leverages its employment-enhancing capabilities (Albanesi et al., 2023, p. 24). Second, labor market regulations such as Product Market Regulation (PMR) and Employment Protection Legislation (EPL) significantly impact AI's labor market effects. Stringent regulations can inhibit the diffusion of AI technologies, moderating their impact on employment. This is evident in countries with restrictive labor policies, where AI adoption is slower and its potential benefits on employment are less pronounced (Albanesi et al., 2023, p. 24).

Educational systems also play a crucial role. Higher levels of educational attainment and positive education outcomes, as indicated by OECD's PISA scores, are associated with greater employment gains from AI. This correlation underscores the importance of a well-educated workforce in adapting to and benefiting from AI technologies. In regions with higher rates of tertiary education, the transition towards AI-enhanced workflows is smoother, leading to increased employment opportunities and economic growth (Georgieff & Hyee, 2021).

These findings showcase that national institutional factors are not merely background conditions but active determinants of how effectively a country can harness the benefits of AI.

Though providing important insight, the above papers don't aggregate the individual national factors they use (e.g. education, labor market structures digitalization and governance) into national system classifications. In other words they account of institutions but not indicators of institutional complementarities such as innovation systems. These would allow for comparative tests amongst different groups of countries, or between more holistic national ecosystems. Kapetaniou and Pissarides (2022) as well as other academics like Hall and Soskice have demonstrated that such factors are significant in terms of how employment systems react to big transitions like robotization and globalization (Thelen 2004; Scharpf and Schmidt 2000; Hall and Sosckice, 2001; Demetriou, 2016). This is precisely the gap that I am trying to fill through this thesis and my main contributions to the literature.

3. Theoretical and Operational Framework

3.1 Defining Artificial Intelligence

The definition of Artificial Intelligence (AI) I will use for my analysis is that of AI as a collection of general-purpose advance computational systems (e.g. natural language modeling, machine learning, machine vision etc.), which have the ability to fulfil tasks that typically require human cognitive functions and emulate or simulate human intelligence (EEF, 2019).

The above definition should not be conflated with the AI applications, such as the use of ChatGPT, or with other technologies, such as robotics. This is because AI applications may in fact be a combination of multiple advance computational systems (for example a tool that use voice commands to generate images would depend on both image generation and voice recognition technologies). Moreover, there is often a confusion between autonomous and/or mobile robotics with AI, thought AI technologies may be used to enable autonomous robotics, it’s important to make the distinction (Felten et. al, 2021, p. 2203). Robotics applications usually involve the manipulation of physical objects and the execution of manual tasks, thus their impact on occupations and employment is quite different form pure AI technologies, and as such should be excepted from a study that tries to capture the impacts of “pure” AI.

Hence, for the purposes of this thesis, occupational exposure to AI means that an occupation’s (or occupational category’s) content is related to (and thus can be affected by) specific advance computational systems which can fulfil tasks that typically require human cognitive functions. Note: In this sense, occupational exposure does not mean AI adoption in a profession or group of professions, what it does mean is that there is a high or low potential (or likelihood) for AI-based automation (Felten et.al, 2021, p. 2197-2198).

3.2 Defining occupations: A task-based approach

Building on the above definition of AI I will define occupations as collections of tasks. This approach is also in line with statistical occupational classifications systems such as the US Standard Occupational Classification (SOC) and the International (and European) Classification of Occupations systems (ISCO/ESCO) (O*NET, 2024; ILO, 2024).

For example, under the ISCO-08 code system, the ‘Economists’ 4-digit occupation class (code 2631) is described as involving 12 tasks, including (ILO, 2024):

(a) Predicting changes in the economic landscape for short-term budgeting, long-term planning, and investment evaluation.

(b) Developing recommendations, policies, and plans for the economy, corporate strategies, and investments, and conducting feasibility studies for projects.

(c) Utilizing mathematical formulas and statistical techniques to test economic theories and solve economic problems.

The occupational class above ‘Economists’, i.e. ‘Social and Religious Professionals’ (ISCO 3-digit code 263), is described as involving 6 tasks, shared with other social science and societal professions such as: psychologists, political scientists and social workers (ILO, 2024). These shared tasks include:

(a) Analyzing and researching past events and activities to understand the origin and evolution of the human race.

(b) Formulating and implementing solutions to current or anticipated economic, political, or social issues.

(c) Providing social services to support individuals and communities.

Furthermore, the occupational class above ‘Social and Religious Professionals’, i.e. ‘Legal, Social and Cultural Professionals’ (ISCO 2-digit code 26), is described as involving 8 tasks, shared with other professions such as:

(a) Conducting research, improving, or developing concepts, theories, and operational methods, or applying knowledge in the field of social sciences.

(b) Conceiving, creating, and performing literary and artistic works.

(c) Developing and maintaining library and gallery collections of archives.

(d) Interpreting and communicating news, ideas, impressions, and facts.

Thus whenever I refer to an occupation or occupational category in this thesis in essence I refer to a collections of tasks or collections of shared tasks respectively, as describe above.

As such, this thesis adopts what the labor economic literature on job automation defines as 'task-based' approach to investigate the research questions of : 'How has the occupational exposure to Artificial Intelligence (AI) affected employment shares in European counties between 2015 and 2019, given institutional complementarity differences?'.

Hence, I build on and further advance the task-based approach of the routine-biased technological change (RBTC) theory (see Autor et.al 2003; Goos et. al, 2014 and others), linking it to AI exposure of occupations in Europe.

3.3 Assumptions

The above approach however comes with some important assumptions that should be considered when interpreting any subsequent results.

3.3.1 The transnational task content of occupations

Firstly, due to data limitations that I will discuss later, and due to the above common occupational definitions across European countries, the task content of all European occupations and occupational categories is considered to be the same as what the ESCO/ISCO system describes, regardless of the country where the occupation is being exercised.

Some of the main variables used are also adaptations from US occupational data, in which case there is again an assumption about US occupations (i.e. occupational task contents) being identical to the European ones and thus about US occupational measures (i.e. AI exposure and offshorability) being applicable and relevant to European occupations. Sections 3.5.3 and 4.4.1 explain how others and I have ameliorated this shortcoming. In addition, there is also an assumption of the degree and nature of AI penetration in the US labour marker being identical to that of the European countries

Though all the above assumptions mean that there are short comings in the analysis results, I consider them to be epistemologically reasonable and in line with similar works in the literature (see for example Albanesi et.al, 2023, p. 10).

3.3.2 Shared averages

Another important assumption in this dissertation comes from the aggregation of my data to average values of the 3-digit occupational categories level (see above example about 3-digit code in section 3.2). This is done due to data-availability limitations I will discuss later on, however it is certainly not a limitation that discredits the validity of my results. In fact, it is in line with other papers in the literature, especially those about European countries (Albanesi et. al 2023 also analyses data at eh 3-digit level and Georgieff & Hyee, 2021 do so at the 2-digit level i.e. on even more generic categories). For reference the 1, 2, 3, and 4-digit levels of the ISCO occupational system consist of 10, 43, 130, and 437 occupational categories respectively (ILO, 2024).

What use of 3-digit averages means for the results of my analysis is that these need to be interpreted as a probabilistic (not actual) impact on the per occupation-employment. This because individual professions only have a share in the task and population content of a category and thus et a proportional share of exposure to AI.

Finally, due to limitation of the data-source I have used for the ‘routine’ measure of my analysis, all occupations under each of the 43 2-digit ISCO codes share the same average routine measure.

3.4 The workings of Institutional Complementarities

I employ two theoretical approaches for the institutional complementarities variables that I will use in my analysis.

As mentioned in section 2.3.3, the relevant literature has shown that accounting only for individual institutional factors is not the same as accounting for systems of institutional complementarities (Thelen 2004; Scharpf and Schmidt 2000; Hall and Sosckice, 2001). The later both capture institutional and inter-institutional dynamics as well as other dynamics like societal, political industrial etc., in doing so they provide more information, but more importantly, they allow for more meaningful country groupings and country group comparisons. That is, if for example one compares the effect of AI exposure on employment between Sweden and Greece, whilst controlling for individual institutional factors (e.g. level of digitalization, and employment benefits), the result reflects the role that digital policy and welfare policy individually have on how AI exposure affects employment, they do not really say something about the interplay between digital and welfare policy, nor do the capture a measure that necessarily reflects the two countries.

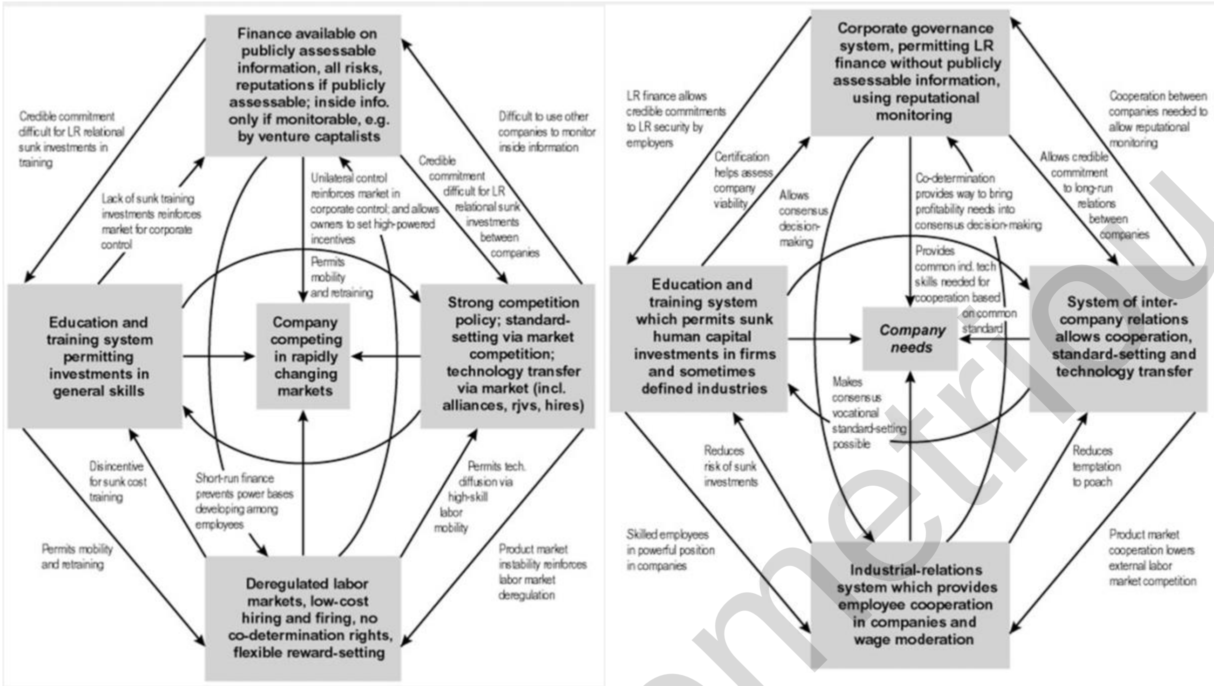
Thus, in order to capture the effect of institutional complementarities, I interchange between two control variables:

My first institutional complementarities control is the innovation system of each EU15 country as a whole. This approach is in line to the one used by Pissarides and Kapetaniou (2022) to capture inter-country differences on the impact that robotization had on employment. They use data from the World Economic Forum's 'Global Competitiveness Report' (Kapetaniou and Pissarides, 2022, pp. 5-6 Klaus Schwab, 2017, and earlier versions) country-level measures of innovation capacity. To create their innovation variable they use the data from the World Economic Forums's Global Competitiveness Report, specifically the measure for 'innovation capacity' which is an average of Quality of scientific research institutions, company spending on R&D, capacity for innovation, collaborations between universities and industry in R&D, government procurement of technology products, and availability of scientists and engineers (Kapetaniou and Pissarides, 2022, pp. 5-6).

I use the 2021 results of the more comprehensive European Innovation Scoreboard's 'Summary Innovation Index' (SII), which includes averages for 32 national measurements organized under 10 categories including: 'linkages', 'digitalization', 'HR', 'intellectual assets' and others (EU Commission, 2021). By accounting for a comprehensive amount of variables that link to technology, employment and systemic linkages the SII is an ideal measure to capture the effect of institutional complementarities on how AI exposure changes occupational employment.

My second institutional complementarities control is the country categorical scale of the so called "Varieties of Capitalism" theory (Hall and Sosckice, 2001). Under the Varieties of Capitalism theory, economies are categorized based on how they organize economic activities and relationships. Three primary categories found in the theory are Coordinated Market Economies (CMEs), Liberal Market Economies (LMEs), and Mixed Market Economies (MMEs). Each type has distinct characteristics regarding the interaction between businesses, workers, and the state (see Appendix section 8.2. for more details on CMEs, LMEs and MMEs).

Figure 1: *Organograms of CME and LME Economies*



Note: Organograms from Hall and Sosckice (2001) illustrating how CME and LME economies operate under their theory.

3.5 Measuring AI’s effect on occupations

Choosing a method of how to measure AI’s effect on occupations is the most important theoretical and operational framework decision in this thesis.

Section 2.3.1 of the literature review explains that there are broadly two approaches to measuring the effect of AI on employment, demand-based approaches and task-based approaches. I have chosen the latter, in this section I will offer a brief comparison of the two approaches to explain my choice. I will then how other researchedr who have used the same measure to apply it to study European countries. Finally, I will then describe the method I have used and explain what the drawbacks, benefits and new contributions of my approach are.

3.5.1 Demand vs Task-Based measurements

The task-based and demand-based approaches offer distinct methodologies for measuring AI occupational exposure. The task-based approach examines the potential for AI to automate specific tasks within various occupations. In essence, this method evaluates test how advancements in AI can substitute tasks traditionally performed by humans, thus showing how AI can job functions and the skills required to execute them (Felten et al., 2018, 2019). In contrast, the demand-based approach assesses the influence of AI on employment by analyzing shifts in labor demand, often using job postings or employment data to infer the impact of AI on labor markets (Georgieff & Hyee, 2021, pp. 11-12, Acemoglu et al., 2020; Squicciarini & Nachtigall, 2021).

Each approach has its strengths and weaknesses. The task-based approach provides a clear picture of which occupations are most susceptible to AI as it allows for a granular analysis of AI's impact on individual job tasks. This can provide insights into how the composition of tasks within jobs might change and the subsequent effects on employment and productivity. Thus, this detailed understanding can help policymakers to mitigate potential negative impacts on employment by focusing on upskilling or reskilling workers for tasks that are less likely to be automated (Autor, 2013).

On the other hand, the demand-based approach is beneficial for capturing broader labor market trends. By examining changes in employment patterns and job postings, this approach can provide a snapshot of how AI is influencing labor demand across different sectors and occupations. However, it lacks the specificity of the task-based approach, firms might train existing employees in AI or outsource AI-related work instead of hiring new staff with AI skills. Furthermore, AI skill demands in job postings may not align with the occupations being automated, leading to potential mismatches in assessing AI's impact on specific jobs (Acemoglu et al., 2020) and may not adequately capture the nuances of how AI affects individual job roles and tasks this is something that the task-based approach can do much more effectively (Georgieff & Hyee, 2021).

Moreover, when evaluating employment effects, the task-based approach is more effective in identifying both substitution and productivity effects. It measures the potential for AI to replace human tasks (substitution effect) and to enhance worker productivity by automating routine tasks (the idea being that it allows workers to focus on higher-value activities). Conversely, the demand-based approach captures these effects only if job postings explicitly require AI skills, potentially missing cases where AI adoption does not necessitate specialized AI competencies (Georgieff & Hyee, 2021, p. 19).

Given the above, I have opted to use the task-based approach for my analysis. Specifically, a measure of the Artificial Intelligence Occupational Exposure.

3.5.2 The AIOE measure

The task-based measure I have chosen specifically is the Artificial Intelligence Occupational Exposure (AIOE) rating that Edward Felten, Manav Raj and Robert Seamans have created and refined (Felten et al., 2018, 2019, 2021).

To create the AIOE measure, they selected the 10 most well-developed AI computational systems applications during the 2010-2015 period (see table below), as rated by the Electronic Frontiers Foundation in a 2019 study (EEF, 2019).

Table 1: *AI computational systems applications*

AI application	Definition
Abstract strategy games	The ability to play abstract games involving sometimes complex strategy and reasoning ability, such as chess, go, or checkers, at a high level.
Real-time video games	The ability to play a variety of real-time video games of increasing complexity at a high level.
Image recognition	The determination of what objects are present in a still image.
Visual question answering	The recognition of events, relationships, and context from a still image.
Image generation	The creation of complex images.
Reading comprehension	The ability to answer simple reasoning questions based on an understanding of text.
Language modeling	The ability to model, predict, or mimic human language.
Translation	The translation of words or text from one language into another.
Speech recognition	The recognition of spoken language into text.
Instrumental track recognition	The recognition of instrumental musical tracks.

Note: Table adapted from Felten et. al, 202, p. 2199.

They then mapped these computational systems to the 52 occupational abilities defined by O*NET (Felten et al., 2021, p. 2199). The did the mapping using survey results sourced from Amazon's Mechanical Turk (mTurk) service, by doing so they created a matrix that quantified the relatedness between AI computational system applications and occupational abilities (Felten et al., 2021, p. 2200). This matrix helped calculate an ability-level exposure score (A_{ij} where i in one of 10 AI computational systems and j is the O*NET occupation ability), as follows:

$$A_{ij} = \sum_{i=1}^{10} x_{ij} \qquad (2)$$

The above exposure score was then aggregated at the occupation level, taking into account the prevalence and importance of each ability within a given occupation (Felten et al., 2021, p. 2201). In the below L_{jk} is the prevalence of an O*NET ability, where k is the occupation and j is the occupational ability; I_{jk} is the importance of an O*NET ability in an occupation; A_{ij} is the same as above.

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}} \qquad (3)$$

The final AIOE score for each occupation was normalized by the sum of the prevalence and importance scores for all abilities required in that occupation, ensuring a balanced measure. Note that, this method does not distinguish between AI as a substitute or a complement to human labor but simply measures the likelihood of exposure to AI (Felten et al., 2021, p. 2202). The final scale was normalized to mean 0 and standard deviation 1, this has results in AIOE also assigning negative values of AI exposure to some occupations, this should not be interpreted as a “reverse exposure” or such occupations being “shielded from AI”, rather the more negative values indicate that an occupation has a relatively low level of exposure to AI.

The authors then validated the AI Occupational Exposure (AIOE) measure through qualitative and quantitative methods. They compared the highest and lowest scoring occupations, finding that white-collar jobs requiring cognitive skills had higher AI exposure, while manual labor jobs had lower exposure (Felten et al., 2021, p. 2202). Detailed case studies were conducted, such as comparing surgeons and meat slaughterers because of a significant overlap in their O*NET abilities. Surgeons, who require high cognitive abilities like problem-solving and reasoning, had significantly higher AI exposure scores than meat slaughterers, who primarily rely on physical skills (Felten et al., 2021, pp. 2204-2205). Another case study compared mathematical technicians and accountants, highlighting how the presence of sensory abilities influenced higher AI exposure for accountants despite similar cognitive demands (Felten et al., 2021, pp. 2206-2207).

3.5.3 Methods for applying the AIOE measure on European countries

As is, the above structure of the AIOE measure presents two main challenges for adaptation to a study for Europe. First, the Standard Occupational Classification (SOC) system used by O*NET is not directly compatible with the European ESCO system (which is identical to ISCO), neither for classifying occupations and occupation-categories nor for matching task content, thus any application to Europe requires some form of "translation" process (known in the literature as 'crosswalks'. Secondly, the AIOE measure was not developed with geographic variations in mind, as O*NET SOC code apply universally to all US states so does the AIOE. This is also the case with ESCO codes and code contents for European countries, there is no per country variation in coding. Thus if a researcher wants an AIOE score per occupation and European country she needs to find a way of deducing how the AIOE measure method can be replicated via a factor that varies by European country. There are two such examples in the literatures Albanesi et. al (2023) and Georgieff & Hyee (2021).

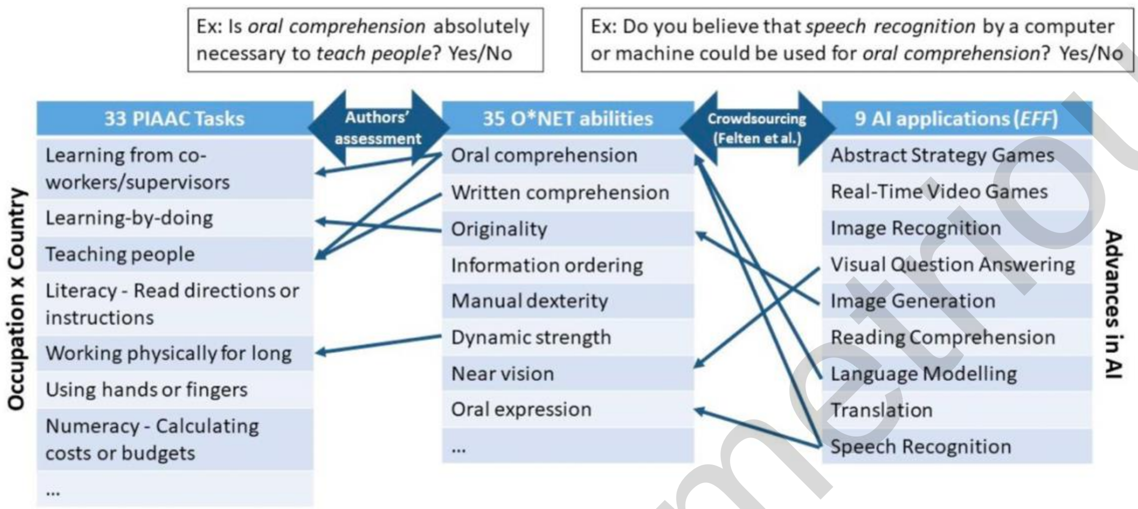
For the translation process Albanesi et. al (2023) have used the crosswalks methodology and relevant correspondence list from Hardy et. al (2018) (Albanesi et. al p. 9). Hardy et. al in-turn utilize 2016 official crosswalks provided by the Institute for Structural Research and the Faculty of Economics at the University of Warsaw (IBS, 2016). Using official crosswalks is very much the standard practice and widely accepted in the literature a statistically robust way to translate SOC classification to ISCO/ESCO classifications. To create country variation within their dataset the authors have converted the AIOE raw occupational scores into percentiles and then weighted by the employment level per occupations-sector cell (Albanesi et. al p. 10). This is practical approach to creating country variation and never before used by other in the literature, however, I consider to have some concerning epistemological flaws. Firstly, by using employment wights the authors imply that employment levels are somehow correlated with AI exposure levels which is neither necessarily the case nor supported by any preceding literature. Furthermore, by incorporating an employment measure into their independent variables whilst measuring employment impact as a depended variable the authors engage in 'circular reasoning' and by extension selection bias, very possibly leading to significant endogeneity in their results. I have thus avoided to use this methodology for my analysis.

A more sophisticated method is that of Georgieff & Hyee (OECD, 2021) who address both the "translation" and country variation problems by mapping O*NET abilities to tasks from the OECD's Survey of Adult Skills (PIAAC) in order to extend the AIOE measure to 23 OECD countries. The linkage process involves associating specific abilities essential for performing given tasks, thus enabling the measurement of AI exposure across various occupations and countries (Georgieff & Hyee, 2021).

This measure is unique as it's not used by either in the literature and both translates data form O*NET to ISCO and accounts for the heterogeneity of occupational task content across countries. Unlike Felten et al. (2019), who define exposure at the occupation level, Georgieff & Hyee scales the measure at the occupation-country cell level, ranging from zero to one, indicating relative AI exposure.

For the mapping between O*NET abilities and PIAAC tasks was manually performed, asking whether an ability is necessary for task to be performed a (see figure below). According to the authors, this process is similar to the Delphi method, it was iterative and driven by consensus, involving multiple rounds of discussion among them (Georgieff & Hyee, 2021, pp. 21-22)

Figure 2: *Method used by Georgieff & Hyee to construct their AIOE measure*



Note: The above figure is used as it appears in Georgieff & Hyee (2021, p. 22).

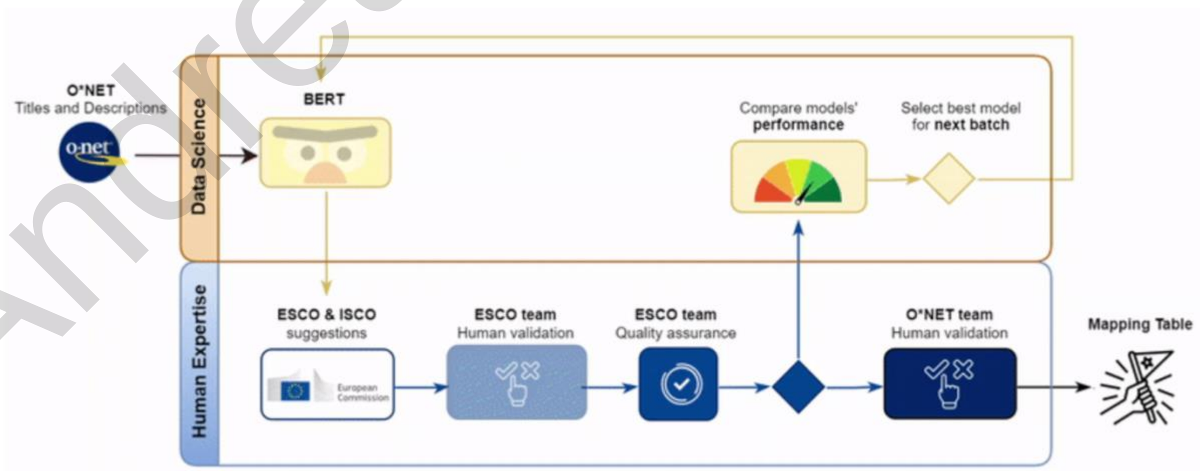
Thought an improvement on the Albanesi et. al approach and being innovative, the above method does have a few short comings: First the PIAAC task content is not as rich as that of O*NET, as result the authors cannot account for 17 out of the 52 O*NET tasks that the AIOE measure of Felten et. al captures as is, this is almost 1 out 3 tasks lost (Georgieff & Hyee, 2021, pp. 21-22). Moreover, there appears to be a significant degree of subjective task matching assessment involved in the above process, the description provided is not detailed enough so as to allow me to comment in the robustness of their method. Despite my efforts (including emailing the authors to better understand the methodology they use) I have not been able to find any further details on this approach besides the above. Hence, I was not able to replicate, test and potentially use this approach. Moreover, the lack of methodological detail also means that the probability for human error in the results is rather uncertain, which is also a considerable drawback.

Given the drawback and restriction in using the above methods I have opted to apply the AIOE data to a European study using a different method.

3.5.4 The method I have used to apply AIOE data to a European study.

Similarly, to Albanesi et. al (2023) in order to "translate" the AIOE US occupation measures to the European ISCO/ESCO measures I am using official crosswalks. Specifically, I chose to use the newest (2022) O*NET-ESCO crosswalks, co-developed by the European Commission and the US Department of Labor's Employment and Training Administration (EU Commission, 2022). This newer version is based on an integration of machine learning and natural language processing used to map European and U.S. occupational classifications between them. This approach utilizes semantic textual similarity models alongside human validation, thus improving how precise the alignment of occupations is. The figure below provides a visual representation of this process:

Figure 3: *The translation process used by the O*NET-ESCO crosswalks*



Note: The above figure is used as it appears in EU Commission's 'The crosswalk between ESCO and O*NET' website (see EU Commission (2022) in references).

The above crosswalks method carries significant advantages compared to the IBS method used by Albanesi et. al. (2023). First, it provides a more up to date translation process that uses data form 2021 and 2022 as opposed to the 2016 data used by the IBS (IBS, 2016). Second, it reduces the chances of human error during translation by incorporating the aforementioned AI techniques whilst maintaining human oversight, at the same time using a more advanced machine technique. Finally, and most importantly, using the above method I was able to translate occupation classes, and by extension the AIOE data, at the very detailed 6-digit ISCO level. This detail has allowed me to preserve much more granularity on the AI exposure level of each individual occupation, and a better match between the task content and circumstances of US occupations with their European counterparts, bringing this improved accuracy into my subsequent analysis. Thus, the use of the O*NET-ESCO crosswalk and the superior translation they provide, is my third and final contribution into literature of the impact of AI occupational exposure on Employment in Europe.

As for capturing country variations, given the shortcomings and lack of accessibility of the approaches described above, as well as time-limitations for developing an original method to use for this thesis, I have opted to keep my occupational variables static across geographies, similarly to Felten et. al (2019), Webb (2020) and Acemoglu et. al (2022).

4. Data and Methodology

In this chapter I present the data sources I have used for my analysis, their individual access limitations and variables I us form each of them. I subsequently explain how I have structured and harmonized these data. Finally, I list the variables that I have constructed (or reconstructed) for the needs of my analysis.

4.1 Main Data Sources and Associated Variables

This thesis uses four main data sources in total, the Artificial Intelligence Occupational Exposure (AIOE) measurements created by Felten et al. (2018, 2019, 2021) (see sections 3.5.2 for more detail); the European Labour Force Survey (Eurostat, 2024); the European Database of Tasks Indices for Socio-Economic Research (Bisello et. al, 2021); and the 2021 European Innovation Scoreboard (EIS) (EU Commission, 2021)[4].

4.2.1 Artificial Intelligence Occupational Exposure (AIOE)

Finding an appropriate dataset for AI measurement was by far the most time-consuming endeavor of this thesis. As previously explained, I use the task-based Aritificial Intelligence Occupational Exposure (AIOE) dataset from Felten et. al (2018, 2019, 2021). The dataset comprised of individual 6-digit-SOC-coded occupations along with their corresponding title and AIOE score. In its raw format the dataset accounts for 774 different SOC-coded occupations. Measures are normalized for mean 0 and standard deviation of 1 ranging from values of -2.67 to 1.58 (this is a ranking, negative values to not imply negative exposure). More details on the measure can be found in section 3.5.2. of the thesis. The dataset is available on GitHub under the name ‘AIOE-Data’[5].

I have used the O*NET-ESCO crosswalks to translate scores of 6-digit SOC occupations to 6-digit ISCO occupations. I have then calculated average values first for the 4-digit and then for

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[4] Data for the EIS can be downloaded from here: https://projects.research-and-innovation.ec.europa.eu/en/statistics/performance-indicators/european-innovation-scoreboard/eis
[5] GitHub link to the AIOE dataset: https://github.com/AIOE-Data/AIOE

3-digit category level (see section 4.3.1), producing 427 and 121 different AIOE measures respectively. I have named the resulting ISCO 3-digit variable 'aioe'. Following exclusions and limitations of my dataset (see section 4.3.2), I have normalized aioe to a zero mean and standard deviation of 1 (in line with Felten et. al, 2021), the resulting variable is named 'aioe_nrm' with clause ranging from -1.766 to 1.671 this is the main independent variable of my analysis.

$$aioe\_nrm$$

Intricately the occupational categories with the highest AIOE scores are:

1. Finance Professionals at 1.321943
2. Mathematicians, Actuaries and Statisticians at 1.286978
3. Financial and Mathematical Associate Professionals at 1.224518
4. Administration Professionals at 1.213954
5. Sales, Marketing and Development Managers at 1.176636
6. Social and Religious Professionals at 1.147596
7. Numerical Clerks at 1.143111
8. Legislators and Senior Officials at 1.126322
9. Street and Related Services Workers at 1.107101
10. Legal Professionals at 1.104921

Conversely the occupational categories with the lowest AIOE scores are:

1. Agricultural, Forestry and Fishery Labourers at -1.190364
2. Painters, Building Structure Cleaners and Related Trades Workers at -1.199131
3. Mining and Mineral Processing Plant Operators at -1.298414
4. Building, Finishers and Related Trades Workers at -1.324737
5. Refuse Workers at -1.369175

6. Vehicle, Window, Laundry and Other Hand Cleaning Workers at -1.398958
7. Domestic, Hotel and Office Cleaners and Helpers at -1.420797
8. Mining and Construction Labourers at -1.475777
9. Blacksmiths, Toolmakers and Related Trades Workers at -1.487173
10. Manufacturing Labourers at -1.504074

The top 10 occupational categories with the highest AI occupational exposure scores include Finance Professionals, Mathematicians, Actuaries, and Legal Professionals. These roles are characterized by tasks that involve complex decision-making, extensive data analysis, and management functions, all of which are increasingly enhanced by AI technologies. These occupations benefit significantly from AI-driven tools, which augment human capabilities, improve efficiency, and enable more informed decision-making processes.

Conversely, the bottom 10 occupational categories, such as Agricultural, Forestry, Fishery Labourers, and Manufacturing Labourers, primarily consist of manual labor and trade jobs. These roles involve physical tasks that are more challenging to automate and thus exhibit a lower AI occupational exposure score. The nature of these tasks makes them less susceptible to AI integration, reflecting the current limitations of AI in replicating human physical activities and manual skills.

4.2.2 European Labour Force Survey (ELFS)

The European Labour Force Survey (ELFS) is a large-scale, continuous yearly survey conducted across households in European Union (EU) member states. Its main goal is to provide detailed and comparable data on the labor market and workforce across Europe.

I use the ELFS in order to derive:

i) The main identifier variable 'ISCO3D', i.e. the 3-digit ISCO occupation category each household belongs to.

ii) The secondary identifier variable 'Country', i.e. the country each respondent household is found in.

iii) The tertiary identifier variable 'Year', i.e. the year each respondent household gave its response in.

Thus, each cell in my dataset is a unique combination of the ISCO3D-Country-Year measures. Moreover, I also use the ELFS to derive:

iv) The dependent variable of my analysis, i.e. Relative Change in Employment Share per 3-digit Occupational Category between 2015-2019. To do so I have calculated the total number of ELFS (employed) respondents per ISCO3D-Country-Year combination and labeled this variable 'rspcnt_20XX'; I have then calculated the total number of ELFS (employed) respondents per Country-Year combination 'emplpop_20XX' and divided the former over the latter to derive the "share" in total employment per year per country that each 3-digit occupational category 'emplpopshr_20XX'. The I have then calculated my dependent variable as follows:

$$Y_{o,c} = \frac{emplpopshr\_2019}{emplpopshr\_2015} \qquad (4)$$

v) I have also used other ELFS variables to construct a series of control variables of the (average) worker characteristic (per 3-digit level). These are: the per category per country per year average gender make-up ‘sex_20XX’; the per category per country per year average highest educational level achieved ‘hat11lev_20XX’; the per category per country per year average degree of household urbanization ‘degurba_20XX’; the per category per country per year average income decile rank ‘incdecil_20XX’; and per category per country per year average age ‘age_20XX’. For each of these variables I represent shifts (difference) in values during the 2015-2019 period, as follows:

$$age\_1519 = age\_2019 - age\_2015 \qquad (5)$$

More detailed description for each of the above ELFS variables can be found at the equivalent survey guides (Eurostat, 2024);

4.2.3 European Database of Tasks Indices for Socio-Economic Research

The ‘European Database of Tasks Indices Across Jobs’, is a system for analyzing the distribution of tasks in the European labor markets. I use the 2021 version of the dataset which is enriched with data from the European Working Conditions Survey (EWCS, 2015), and the OECD's PIAAC Survey (OECD, 2020), these are combined providing a detailed taxonomy of the tasks, methods, and tools that different occupations use (Fernández-Macías and Bisello, 2020). The database only has data for 2020 and the EU15 countries. It categorizes tasks into physical, intellectual, and social dimensions, and includes sub-categories based on specific activities and required skills. This framework allows for insights into how tasks are grouped in different occupation categories (Fernández-Macías et al., 2016a, 2016b).

Table 2: *Task Taxonomy for work, method and tool content*

A. In terms of the content:

1. **Physical tasks:** aimed at the physical manipulation and transformation of material things:
    a. *Strength:* lifting people and heavy loads, exercising strength.
    b. *Dexterity:* precisely coordinated movements with hands or fingers.
    c. *Navigation:* moving objects or oneself in unstructured or changing spaces
2. **Intellectual tasks:** aimed at the manipulation and transformation of information and the active resolution of problems:
    a. *Information processing:*
        I. Visual and/or auditory processing of uncodified/unstructured information
        II. Processing of codified information
            i. Literacy:
                a. Business: read or write letters, memos, invoices, ...
                b. Technical: read or write manuals, instructions, reports, forms, ...
                c. Humanities: read or write articles or books.
            ii. Numeracy:
                a. Accounting: calculate prices, fractions, use calculators, ...
                b. Analytic: prepare charts, use formulas or advanced maths
    b. *Problem solving:*
        I. Information gathering and evaluation.
            i. Information search and retrieval
            ii. Conceptualization, learning and abstraction
        II. Creativity and resolution
            i. Creativity
            ii. Planning/implementation
3. **Social tasks:** whose primary aim is the interaction with other people:
    a. *Serving/attending:* responding directly to demands from public or customers
    b. *Teaching/training/coaching:* impart knowledge or instruct others
    c. *Selling/influencing:* induce others to do or buy something, negotiate
    d. *Managing/coordinating:* coordinate or supervise the behaviour of colleagues
    e. *Caring:* provide for the welfare needs of others.

B. In terms of the methods and tools of work:

1. **Methods:** forms of work organisation used in performing the tasks:
    a. *Autonomy*
        I. Latitude: ability to decide working time, task order, methods and speed.
        II. Control (in reverse): direct control by boss or clients, monitoring of work.
    b. *Teamwork:* extent to which the worker has to collaborate and coordinate her actions with other workers
    c. *Routine*
        I. Repetitiveness*:* extent to which the worker has to repeat the same procedures
        II. Standardisation: extent to which work procedures and outputs are predefined and encoded in a formalised system
        III. Uncertainty (in reverse): extent to which the worker needs to respond to unforeseen situations
2. **Tools:** type of technology used at work:
    a. *Non-digital machinery (analog)*
    b. *Digitally-enabled machinery*
        I. Autonomous (robots)
        II. Non-autonomous
            1. Computing devices
                a. Basic ICT (generic office applications)
                b. Advanced ICT (programming, admin)
                c. Specialised ICT
            2. Others

Note: Table sourced from Bisello et. al, 2021, p. 10.

The dataset comprises of occupational averages on the 2-digit ISCO level, and it is the dataset that I use to extract the 'routine' measure of my analysis. More, specifically the 'routine' measure comprises of measurements for the degree of 'repetitiveness', 'standardization' and 'certainty' of different ISCO 2-digit categories (see table 2 above).

Both the inclusion of routine and the fact that the routine measurement used in my analysis is sourced from European respondents, are unique to the literature of AI employment automation in Europe and thus constitute another contribution to literature. This is a pivotal control variable used in most major studies of the impact of automation on employment during the last two decades (Goos et. al 2007, 2014; Autor D. & David D. 2013; Autor et. al , 2003, 2015).

To create the exact variable I use in my analysis, I have normalized all the “task-content” and all the “method/tool” tasks from 0 to 1 for each 2-digit occupational category, effectively creating percentage measures (in decile terms) for each category in the “task-content and “method-tool” lists as seen in Table 2.

Hence, ‘routine’ in the below analysis represents the average percentage share of how much routine the form of work organization of each occupational category contains, compared to other methods and tools used in the EU15 countries.

$$'routine'$$

In my analysis below I also use other variables from the dataset, namely ‘machines’ which represents the percentage of average analog machinery use in each occupational category; ‘ict’ which represents the percentage of average use of computing devices in each occupational category; and ‘ictadvanced’ which represents the percentage of average use of advanced computing (e.g. programmins) in each occupational category. I use these variables to test the results of my regression when I exchange the ‘aioe_nrm’ measure for each one of these and when I control for them, this link my regression results to studies on previous waves of automation.

4.2.4 The European Innovation Scoreboard

The European Innovation Scoreboard uses a structured framework that divides innovation into four primary activities: ‘Framework Conditions’, ‘Investments’, ‘Innovation Activities’, and ‘Impacts’ (see Table3). These activities are further broken down into 12 dimensions and are assessed using 32 indicators (EU Commission, 2021). Each category is equally weighted in calculating the Summary Innovation Index (SII) (European Commission, 2021). The purpose of the framework is to help EU members to find areas needing improvement to enhance their innovation performance. The EIS data is sourced from entities like Eurostat and the OECD, thus ensuring consistency and comparability across the different EU countries. The data in the scoreboard vary by year and by country.

The only variable I use from this dataset is the Summary Innovation Index (SII), more specifically I calculate the difference in the values SII measurement at the start of my analysis period (2015) and at the end (2019). The variable appears as '_sii_1519'.

Table 3: The shift in the Summary Innovation Index (SII) score per country between 2015-19.

Country	**SII 2019 score**	**SII 2015 score**	**Difference ('_sii_1519')**
Austria	124.312	123.598	0.714
Belgium	129.26	122.347	6.913
Denmark	137.787	133.251	4.536
Finland	133.028	127.318	5.71
France	114.236	115.841	-1.605
Germany	121.606	120.156	1.45
Greece	72.187	63.982	8.205
Ireland	123.225	123.316	-0.091
Italy	89.869	82.368	7.501
Luxembourg	129.705	128.679	1.026
Netherlands	137.168	130.957	6.211
Portugal	93.752	85.151	8.601
Spain	90.469	87.081	3.388
Sweden	138.177	135.486	2.691

United Kingdom	128.521	123.269	5.252

Notes: Author’s calculations from EIS data.

Table 4: *The breakdown of the EIS framework*

FRAMEWORK CONDITIONS

- Human resources
  - 1.1.1 New doctorate graduates (in STEM)
  - 1.1.2 Population aged 25-34 with tertiary education
  - 1.1.3 Lifelong learning
- Attractive research systems
  - 1.2.1 International scientific co-publications
  - 1.2.2 Top 10% most cited publications
  - 1.2.3 Foreign doctorate students
- Digitalisation
  - 1.3.1 Broadband penetration
  - 1.3.2 Individuals who have above basic overall digital skills

INVESTMENTS

- Finance and support
  - 2.1.1 R&D expenditure in the public sector
  - 2.1.2 Venture capital expenditures
  - 2.1.3 Direct government funding and government tax support for business R&D
- Firm investments
  - 2.2.1 R&D expenditure in the business sector
  - 2.2.2 Non-R&D innovation expenditures
  - 2.2.3 Innovation expenditures per person employed in innovation-active enterprises
- Use of information technologies
  - 2.3.1 Enterprises providing training to develop or upgrade ICT skills of their personnel
  - 2.3.2 Employed ICT specialists

INNOVATION ACTIVITIES

- Innovators
  - 3.1.1 SMEs with product innovations
  - 3.1.2 SMEs with business process innovations
- Linkages
  - 3.2.1 Innovative SMEs collaborating with others
  - 3.2.2 Public-private co-publications
  - 3.2.3 Job-to-job mobility of Human Resources in Science & Technology
- Intellectual assets
  - 3.3.1 PCT patent applications
  - 3.3.2 Trademark applications
  - 3.3.3 Design applications

IMPACTS

- Employment impacts
  - 4.1.1 Employment in knowledge-intensive activities
  - 4.1.2 Employment in innovative enterprises
- Sales impacts
  - 4.2.1 Medium and high-tech product exports
  - 4.2.2 Knowledge-intensive services exports
  - 4.2.3 Sales of product innovations
- Environmental sustainability
  - 4.3.1 Resource productivity
  - 4.3.2 Air emissions by fine particulates PM2.5 in Industry
  - 4.3.3 Development of environment-related technologies

Note: Table sourced from the 2023 EIS Methodology Guide.

4.3 Created Variables

In order to replicate exact control variables found in the literature I had to construct the Offshorability measure they use for each 3-digit occupational category using US data. To do so I have first downloaded O*NET's 28.2 version of the Work Activity dataset (O*NET, 2024b), this dataset has given me value scores for the 'Importance' and 'Level' of each task in the group of tasks making up a SOC-code occupation. I have then adapted this as per Firpo et all (2011) i.e. weight of two thirds to "importance" and one third to "level" in using a weighed sum for work activities in the O*NET Task scores. The Work Activity dataset however was missing one of the tasks the 'Face-to-face discussions'. To overcome this shortcoming I sourced this task-content from the Work Context dataset.[6] I then derived a single value per 'Face-to-face discussions' task row and created a relevant dataset combining this with the Work Activity dataset values. The above process has given me Non-Offshorability index measure. The constituent data are time invariant, and thus so is the resulting index.

I then normalized the range of values for each task form 0 to 1 across occupations. Following this I calculated one average value for all the Non-offshorability task per profession to derive a single normalized average Non-offshorability score per occupation. I then used the of ONet-ESCO crosswalks (see section 3.5.4) to map these Non-offshorability task values to the ISCO codes. I then compiled the normalized average of Non-offshorability scores down to the 4-digit, 3-digit, and 2-digit level. Finally, I subtracted the normalized Non-offshorability values from 1 to created the 'offshorability' measure I use in my below analysis.

$$'offshorability' = 1 - 'non\ offshorability'$$

[6] Link to O*NETs Work Context dataset: https://www.onetcenter.org/database.html#ctx

4.4 Exclusions, Data Structuring and Harmonization

In this section I outline how I have structured and harmonized the dataset I have used for my analysis. I then explain what has been excluded due to availability or methodological reasons.

4.4.1 Structuring and Harmonization

Given the limitations of the ELFS data I had access to (see section 4.2.2), I have aggregated all my datasets to averages at the 3-digit ISCO level, that is the values for all households that shared the same 3-digit ISCO code-country-year combination. I have first merged the data sets for each country-year combination into country datasets (see Python code in section 8.3 of the Appendix for reference). I subsequently merged all the country datasets into a single ELFS dataset organized in ISCO 3-digit-country-year combination rows. I have added to this dataset the AIOE values for each ISCO 3-digit occupational category along with a measure of offshorability.

4.4.2 Exclusions and Limitations

Following the translation of the AIOE dataset form US to EU data the 3-digit ISCO category 323 ('Traditional and complementary medicine associate professionals') could not be translate over, this is also the case for the offshorability variables, it was thus excluded from the analysis.

Due to the data available by the University of Cyprus I only had access to ELFS microdata up to 2020 and only with 3-digit level occupational categories (4-digit level data are only available to PhD students and academic personnel), data at the 6 and 8-digit level are only available after seeing through an application process for access to Eurostat, which was beyond the time scope of this thesis. For context, the above mean that I am able to know the responses of the code of a specific household in the data, but I cannot know the exact occupation these replies correspond to (e.g. 'Economist' code 2631), I only know the 3-digit occupational category the replies correspond to (e.g. 'Social and Religious Professionals' code 263). Moreover, as delivered, the dataset is missing ISCO category 63 for 'Subsistence Farmers, Fishers, Hunters and Gatherers' and the 3-digit category 224 ('Paramedical Practitioners') (this is also missing from other datasets because of the O*Net to ISCO Crosswalks methods used).

From the ELFS dataset I have excluded the ISCO 63, ISCO 224 and ISCO 999 categories (the latter corresponds to household which do not participate in the labour force notably constituting about 50% of ELFS respondents).

Finally, the 'European Database of Tasks Indices for Socio-Economic Research' excludes category 0 of the ISCO system (i.e. 2-digit ISCO codes 0X, 3-digit ISCO codes 0XX etc.), that is the armed forces, thus these occupations are also excluded.

Thus the end-result dataset contains data for 121 3-digit occupational categories and the EU15 group of countries (i.e. Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom), for the 2015 - 2019 period.

5. Empirical Analysis

5.1 Descriptive Statistics

5.1.1 Histogram of the main variables

It can be seen that the normalized AIOE measure exhibits a negligible negative bias, it should nevertheless be reiterated that the variable ranks the exposure of occupational categories to AI and does not assign a value of an incompatibility of occupation with AI, hence negative values indicate a lower rank not an inverse relationship.

Figure 4: Histogram of the normalized Artificial Intelligence Occupational Exposure

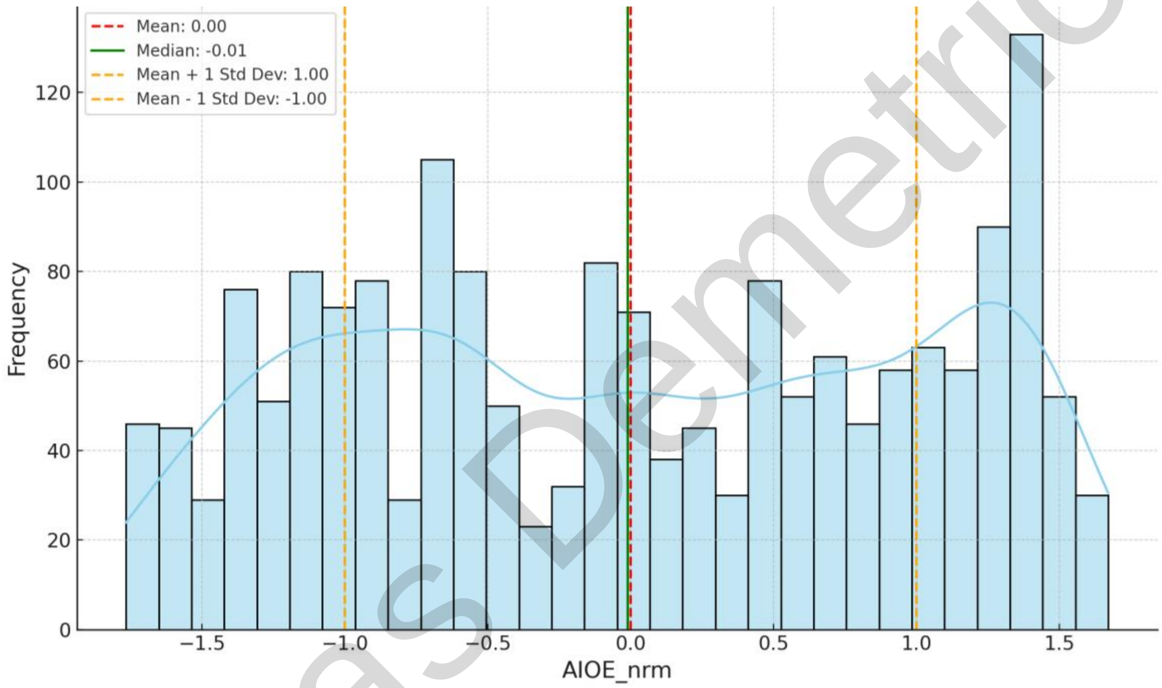


Figure 5: Histogram of occupational routine content measure.

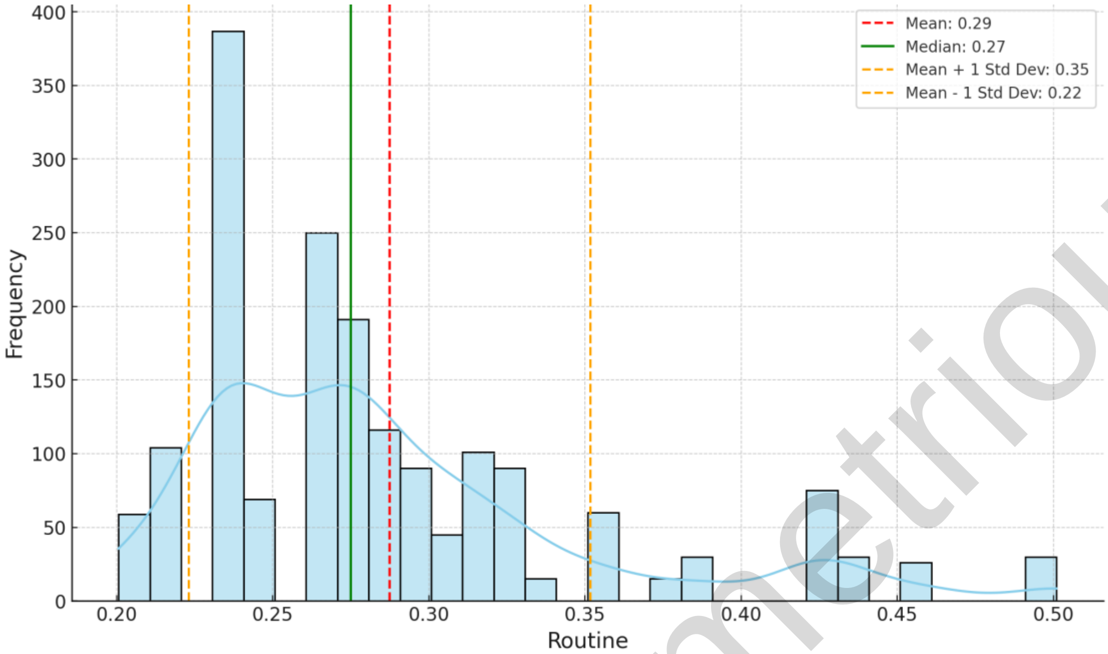
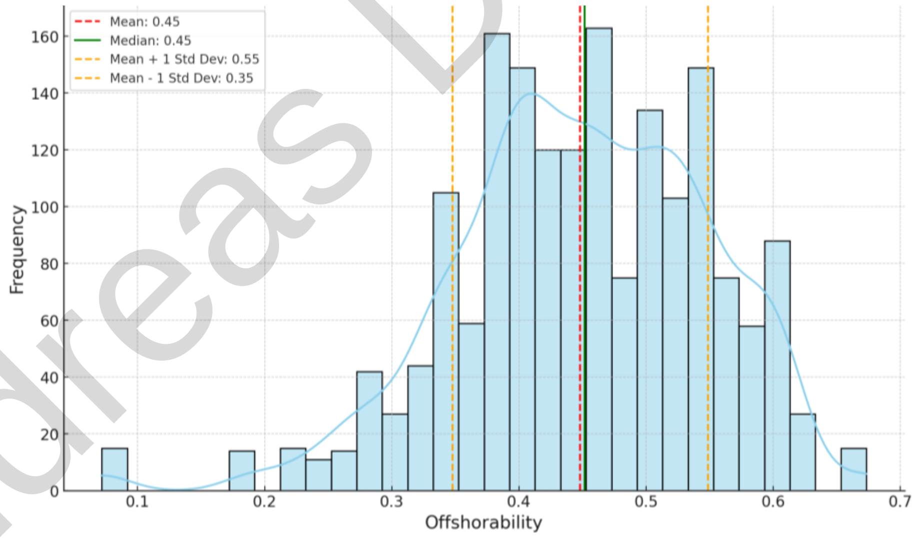
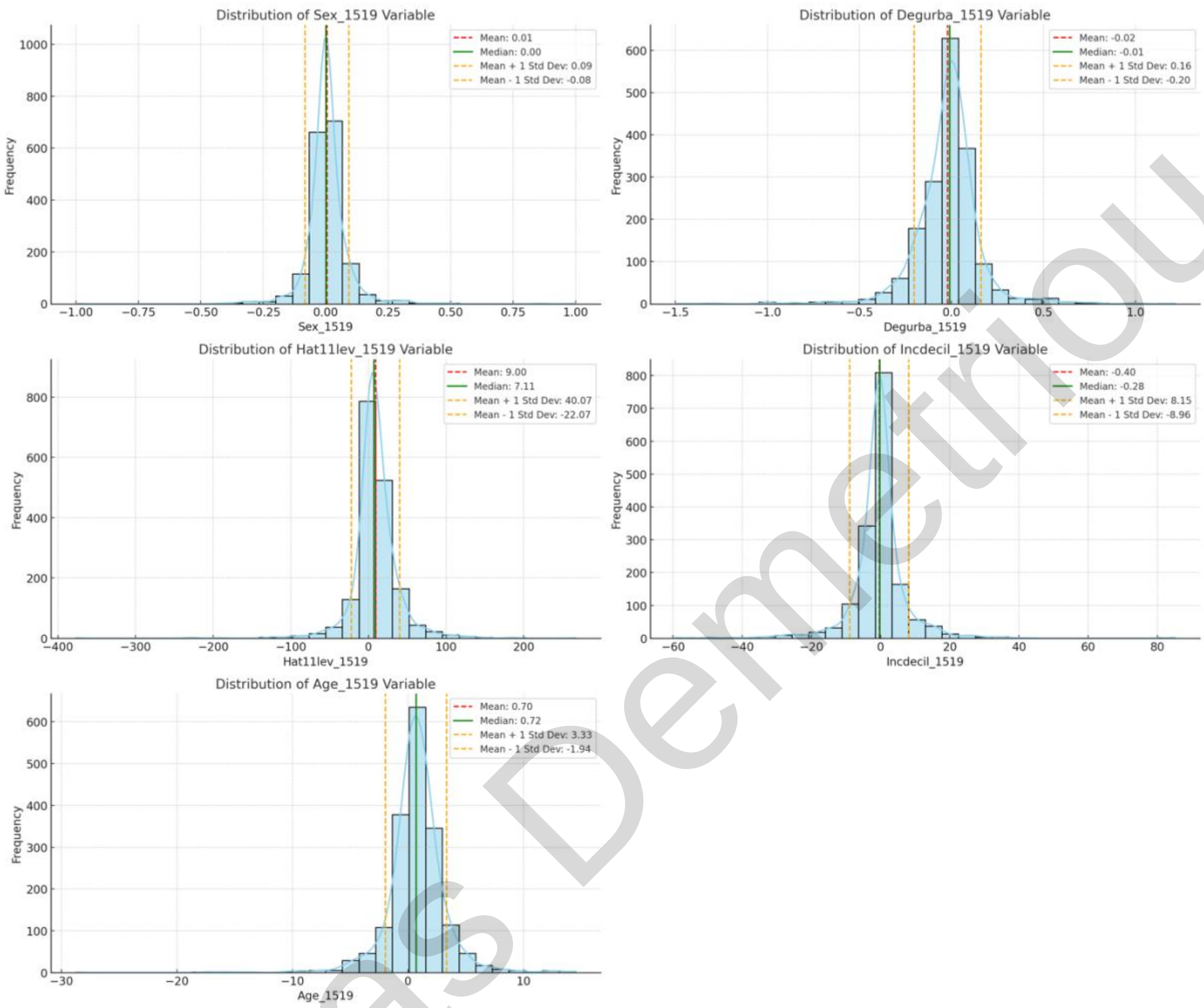


Figure 6: Histogram of occupational offshorable content measure, normalized between 0 to1.



The below histograms for the worker-level variables indicate that during the 2015 to 2019 period shifts in the profile of the average worker per occupational category were minimal.

Figure 7: Histogram of values difference shift in occupational gender-mix, urbanization level, higher educational level, income decil and average age during the 2015-19 period.



5.1.2. Scatterplots of the main variable interactions with the dependent variable

As it can be seen from Figures 8, 9, and 10,

Figure 8: Scatterplot between the change in employment share and AI occupational exposure.

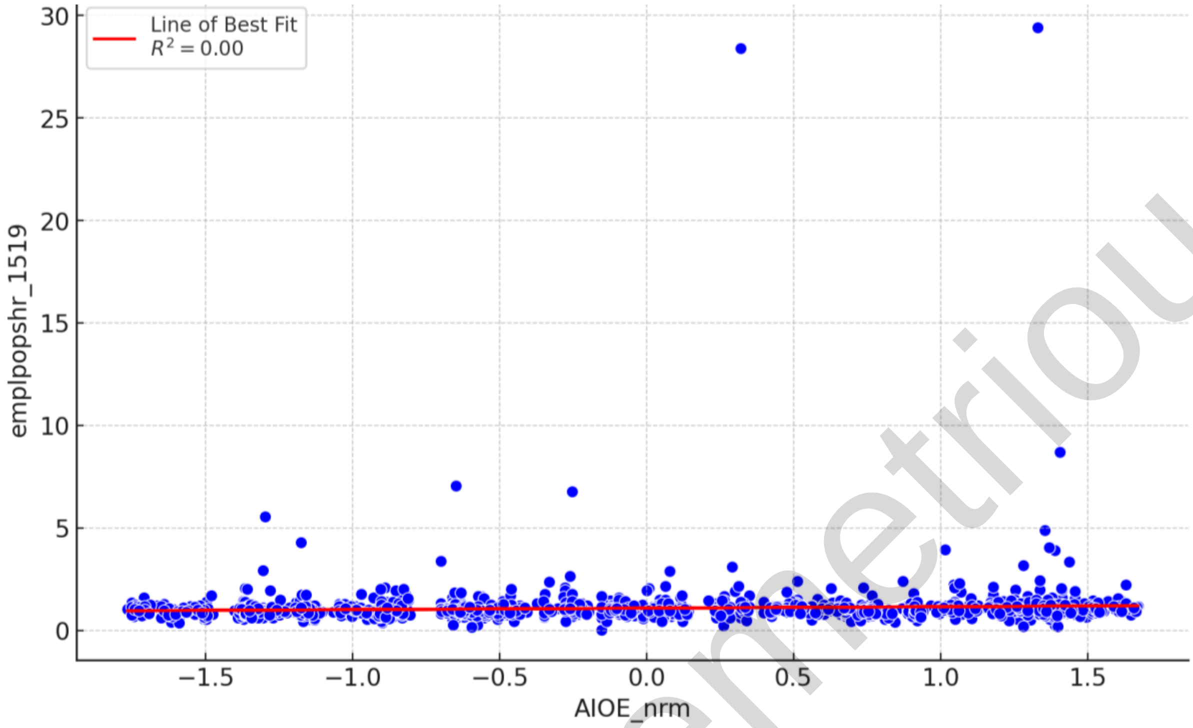


Figure 9: Scatterplots between the change in employment share and occupation-level characteristics.

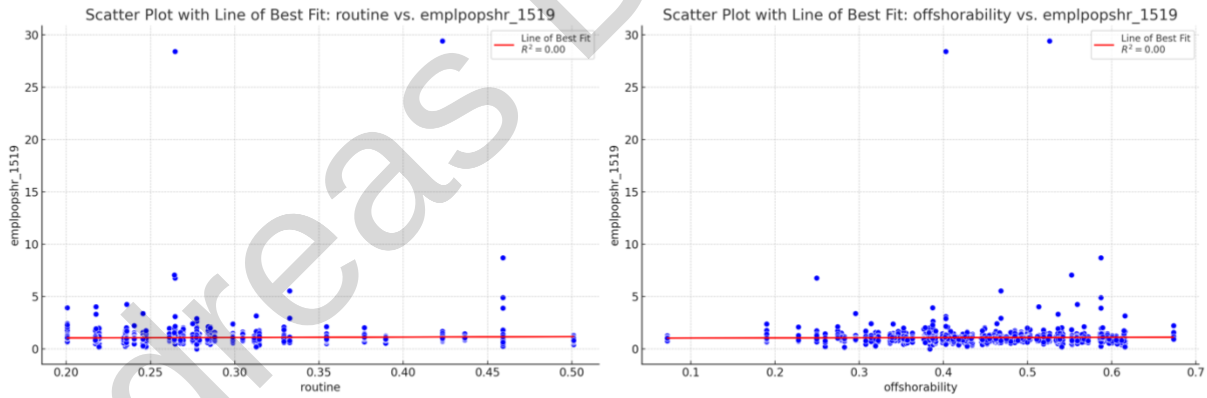
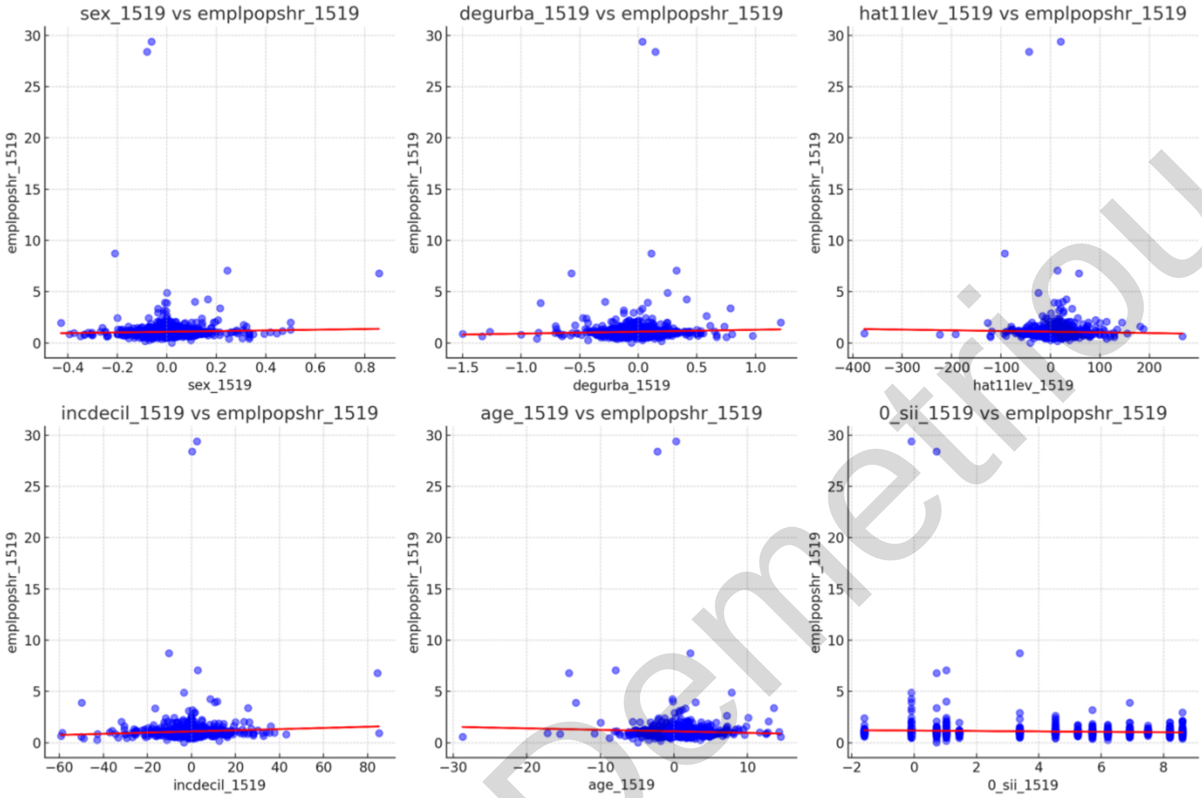
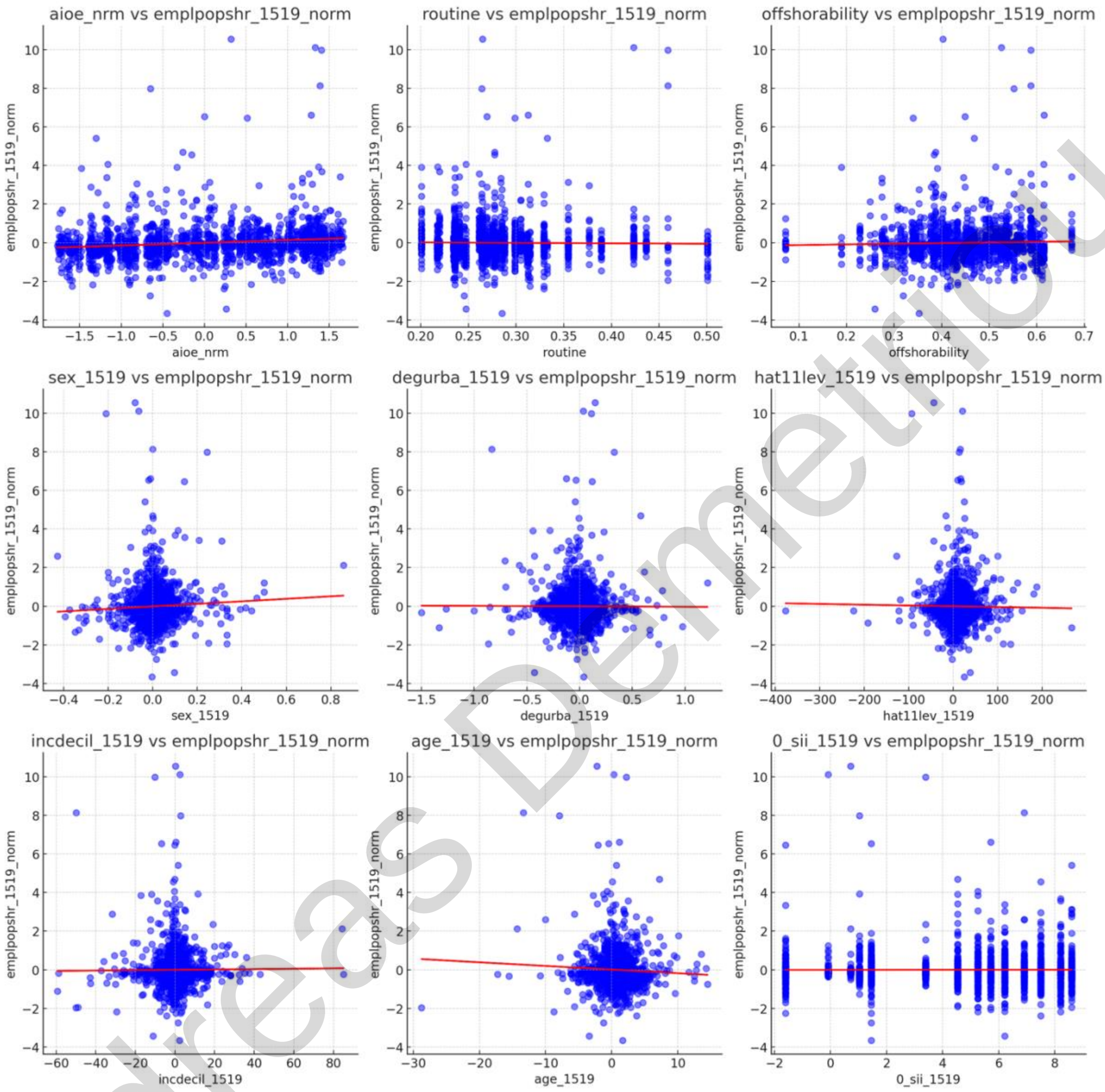


Figure 10: Scatterplots between the change in employment share vs worker-level characteristics.



When normalizing the employment share change, as it can seen in Figure 1, AI occupational exposure, as well as occupation and worker-level characteristics, despite small changes during the studied period, show more noteworthy variability during this in the employment share changes relative to their respective means.

Figure 11: Scatterplots between the normalized change in occupational employment shares vs AI occupational exposure, worker and occupation-level characteristics.



5.1.3 Summary Statistics of main Variables

Table 5: Summary Statistics of key variables.

Variable	Obs	Mean	Std. dev.	Min	Max
emplp~r_1519	1,765	1.084	1.037	0.018	29.409
aioe_nrm	1,783	0.000	1.000	-1.766	1.671
routine	1,783	0.287	0.064	0.201	0.501

offshorab~ty	1,783	0.448	0.101	0.072	0.673
sex_1519	1,765	0.005	0.088	-1.000	1.000
degurba_1519	1,765	-0.021	0.181	-1.500	1.214
hat11l~_1519	1,765	8.999	31.072	-376.889	266.667
incdec~_1519	1,632	-0.403	8.557	-59.333	85.111
age_1519	1,765	0.696	2.637	-28.750	14.500
_sii_1519	1,784	4.051	3.124	-1.605	8.601

5.2. Statistical Robusteness Tests

5.2.1. Multicollinearity

Multicollinearity levels have been low in all the different regression models I have run regardless of the combination of variables. The below Variance Inflation Factor (VIF) table is an indicative result, showing VIF values close to 1 and tolerance level (i.e. 1/VIF) below 1, indicating negligible levels of multicollinearity

Variable	VIF	1/VIF
offshorab~ty	1.15	0.865913
routine	1.09	0.918266
aioe_nrm	1.07	0.935582
incdec~_1519	1.05	0.949545
age_1519	1.05	0.953451
sex_1519	1.05	0.954584
hat11l~_1519	1.04	0.963904
degurba_1519	1.02	0.981139
_sii_1519	1.01	0.988193
Mean VIF	1.06	

5.2.2 Heteroskedasticity

Upon running the first regression of my analysis I have detected heteroscedasticity in all the different regression models I have run, as Breusch-Pagan test results where statistically significant with values close to zero. Hence, all reported regression results in the thesis use robust standards errors to ameliorate for this.

5.2.3 Endogeneity

From a theoretical perspective the possibility for endogeneity is not high enough to render relevant tests and subsequent use of instruments. This is especially the case for the AI exposure the employment share relationship, as the AIOE measures are from the US and occupation measures from Europe, hence their cannot be real life a transmission mechanism by which connect the two, their connection is probabilistic in this sense (Albanesi et. al. 2023, p. 10)

5.3 Empirical Strategy

In this section I outline the steps I have taken when developing the regression model of my analysis.

5.3.1 Employment Share and AI Occupational Exposure

I have started from a regression between the employment share and the AI Occupational Exposure variables:

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \varepsilon_{o,c} \qquad (5)$$

5.3.2 Adding Occupational Characteristics

I have then added the occupational characteristics of routine and offshorability as potential controls:

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \gamma_1 O_o + \varepsilon_{o,c} \qquad (6)$$

5.3.3 Adding Worker Characteristics

I subsequently included fundamental worker characteristics of gender, income, and age composition per occupational category as further potential controls:

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \gamma_1 O_o + \gamma_2 W_{o,c} + \varepsilon_{o,c} \qquad (7)$$

5.3.4 Adding country innovation score interactions

Similarly to Kapetaniou and Pissarides (2022), I subsequently added the average country innovation scores for the 2015-2019, which I test through an interaction with the 'aioe_nrm' variable.

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \gamma_1 O_o + \gamma_2 W_{o,c} + \beta_2 (AI_o * S_c) + \varepsilon_{o,c} \qquad (8)$$

5.3.5 Adding Country Dummies

I then I omitted the country innovation interaction measurement for generated dummy (indicator) variables for each country (excluding Austria, as a reference country is required). Adding these dummies allows to control for any unobserved, country-specific, time-invariant factors that might affect the dependent variable. This allows the model to isolate the effects of the observed variables more accurately by adjusting for differences in baseline levels across countries:

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \gamma_1 O_o + \gamma_2 W_{o,c} + \delta_3 D_c + \varepsilon_{o,c} \qquad (9)$$

5.3.6 Adding Varieties of Capitalism Dummies

I have then replaced the country dummies with dummies for three groupings of different Varieties of Capitalism system (i.e. Central Market Economy, Mediterranean Market Economy and Liberal Market Economy):

$$Y_{o,c} = \beta_0 + \beta_1 AI_o + \gamma_1 O_o + \gamma_2 W_{o,c} + \delta_4 VD_c + \varepsilon_{o,c} \quad (10)$$

As mentioned above, I use robust standard errors in all the regressions as there was heteroscedasticity in my original results.

5.4 Final Results and Interpretation

The below table lists all the regression results from all the models presented in section 5.3 .

Model Section:	(5.3.1)	(5.3.2)	(5.3.3)	(5.3.4)	(5.3.5)	(5.3.6)
AIOE	0.072***	0.073***	0.077***	0.151**	0.077***	0.077***
	(0.025)	(0.023)	(0.025)	(0.065)	(0.025)	(0.025)
Routine		0.347	0.311	0.318	0.278	0.309
		(0.568)	(0.631)	(0.633)	(0.617)	(0.628)
Offshorability		-0.115	-0.134	-0.141	-0.135	-0.139
		(0.146)	(0.153)	(0.154)	(0.152)	(0.154)
Change in occupational Gender-mix			0.180	0.222	0.216	0.188
			(0.538)	(0.528)	(0.523)	(0.540)
Change in household urbanization-level			0.173	0.175	0.182	0.149
			(0.168)	(0.169)	(0.188)	(0.170)
Change in higher educ level			-0.000	-0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.001)	(0.001)
Change Income			0.005	0.005	0.008	0.005
			(0.004)	(0.004)	(0.005)	(0.004)
Change in Age			-0.015	-0.015	-0.019	-0.014
			(0.014)	(0.014)	(0.014)	(0.014)
Innovation Interaction				-0.018*		
				(0.010)		
Austria					0.000	
Belgium					-0.254	

Denmark					-0.223	
Finland					-0.274	
France					-0.310	
Germany					-0.331	
Greece					-0.265	
Ireland					0.208	
Italy					-0.290	
Luxembourg					-0.257	
Netherlands					-0.291	
Portugal					-0.240	
Spain					-0.172	
UK					-0.330	
CME						0.000
MME						0.107
LME						-0.026
_cons	1.084***	1.036***	1.080***	1.080***	1.308***	1.069***
	(0.025)	(0.163)	(0.194)	(0.194)	(0.370)	(0.220)
N	1764	1764	1616	1616	1616	1616
r2	0.005	0.005	0.010	0.013	0.027	0.012

The above results showcase that the occupational exposure to artificial intelligence is statistically significant regardless of the model interaction used. For every 1-point increase in the rank of an occupation in the AIOE scale there is a 7% increase in the employment share of that occupational category during the 2015-2019 period.

Interestingly the changes in occupational control variables and worker characteristic variables do not seem to have affected changes in employment levels.

This result likely reflect a fundamental difference in the nature of the influence of AI on employment during this period, compared to other technologies in previous waves of automation where factors such as job routine and offshorability were more prominent.

The below table showcases the results for the aforementioned regressions models but with a normalized version of the employment share change measurement, which, as indicated by Figure 11 above, captures more of the variability in the chosen models. The most notable difference is that the routine becomes statistically significant, indicating that the routine content of a profession is negatively associated with employment share (as shown by the literature on previous waves of automation). Specifically, for each one-point increase in the routine content of an occupational category there is a negative standard deviation movement in employment share of that occupational category.

Moreover, the change in a more female occupational gender-mix appears to be positively associated with employment share.

Finally, the interaction of innovation country scores and AI occupational exposure is also statistically significant in this variation of the main models. Unlike, the case of robotic automation, AI exposure appear to have a slight negative impact in employment growth in countries were innovation scored increased.

	(5.3.1)	**(5.3.2)**	**(5.3.3)**	**(5.3.4)**	**(5.3.5)**
AIOE	0.105***	0.109***	0.104***	0.180***	0.104***
	-0.022	-0.022	-0.023	-0.035	-0.023
Routine		-1.395***	-1.261***	-1.252***	-1.265***
		-0.391	-0.398	-0.399	-0.399
Offshorability		0.172	0.074	0.068	0.074
		-0.236	-0.244	-0.244	-0.245
Change in occupational Gender-mix			0.634**	0.676**	0.649*
			-0.322	-0.319	-0.331

Change in household urbanization-level			0.025	0.027	0.018
			-0.134	-0.134	-0.141
Change in higher educ level			-0.001	-0.001	-0.001
			-0.001	-0.001	-0.001
Change Income			0.002	0.002	0.002
			-0.003	-0.003	-0.003
Change in Age			-0.01	-0.009	-0.011
			-0.01	-0.01	-0.01
Innovation Interaction				-0.018***	
-0.007					
Austria					0
Belgium					0
Denmark					0.013
Finland					-0.024
France					-0.001
Germany					0.003
Greece					0.033
Ireland					0.089
Italy					0.007
Luxembourg					0.021
Netherlands					0.02
Portugal					0.024
Spain					0.002
UK					-0.006
_cons	0	0.324***	0.347**	0.346**	0.336*
	-0.023	-0.123	-0.136	-0.137	-0.179
--------	------------- ------	-------------	--------------- -	--------------- -	--------------- -
N	1781	1781	1631	1631	1631
r2	0.0111486	0.0186528	0.0223704	0.0259308	0.0229775

5.4 Discussion: Possible Real-World and Policy Implications

The above results indicate that employment automation is likely to have a positive employment effect on high skill professions with a significant mathematical or text analysis content (see sections 4.2.1 and 5.4), a result that is in agreement with others in the literature. Similarly, to previous waves of automation, routine content of occupations seems to be negatively associated with employment share however, unlike previous waves of automation (such as robotization) an increased level of country innovation does not seem to have an ameliorating effect on the impact of AI as an automation technology. In addtition, a relative increase in female participation in an occupational category also appears to have a positive employment effect on employment when controlling for AI exposure.

Finally, increase in AI exposure appears to positively affect employment share even when factors such as country innovation, gender mix and routine content of an occupational category are controlled for. This implies that policymakers have no strong reason to be concerned about eh possible effects of AI, at least regarding eh application of technologies such as image recognition, language procession, translation and abstract strategy.

6. Concluding Remarks

This thesis has contributed to the growing body of literature on the impact of artificial intelligence (AI) on employment, specifically within the EU15 countries during the period of 2015-2019. By utilizing the Artificial Intelligence Occupational Exposure (AIOE) measure, this study has provided an empirical analysis that captures the nuanced ways AI influences employment shares of occupations in Europe.

The contribution of this thesis lies in three points, on it the use of a more precise method of translating the US SOC categorization tot eh European ISCO/ESCO categorizations, thus allowing for more accurate application of the main independent variable the AI occupational exposure. Moreover, by using data from the European Database of Tasks Indices for Socio-Economic Research, the thesis offers a unique European perspective, differentiating itself from studies that rely heavily on US data.

Furthermore, the inclusion of controls for occupational routine and the differentiation between European and US occupational classifications enriches the analysis, making it more relevant and accurate for the European context. This approach has enabled the thesis to draw comparisons between technological automation in past industrial revolutions and the current AI-driven changes, bridging a gap in the literature by linking historical and contemporary findings.

Another significant contribution is the examination of the role of institutional complementarities in moderating the impact of AI on employment. Specifically, by incorporating proxies for innovation and political economy types of institutional complementarities, the study test for the importance of national institutional contexts in shaping the effects of AI on labor markets. This aspect of the research not only adds depth to the understanding of AI's impact on employment but also aligns it with well-established insights from institutional and labor economics.

The empirical findings of this thesis reveal that AI exposure has a statistically significant impact on employment shares, particularly in high-skill occupations. The results indicate that countries with more advanced digital infrastructures and higher innovation capacities do not necessarily experience more substantial positive impacts from AI-enabled automation as intuition would suggest.

In conclusion, this thesis advances the academic discourse on AI and employment. It underscores the importance of considering both the specific tasks within occupations and the broader institutional contexts when assessing the impact of AI on employment. The findings contribute to a deeper understanding of how AI is reshaping labor markets in Europe, but also offer valuable insights for policymakers who may be unduly unconcerned with potential negative impacts of AI technologies.

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8. APPENDIX

8.1 Comparison of SOC, ISCO, ESCO tasks

The table below is an indicative comparison of the definitions of the tasks of the Economists occupation under the US SOC, European ESCO and International ISCO systems (BLS, 2024; European Commission, 2024; ILO, 2024):

Task Description	SOC	ESCO	ISCO
Research Economic Issues	Research economic issues related to education, labor force, international trade, and other topics	Conduct research on economic phenomena, including collecting and analyzing data	Conduct research and develop models to understand economic phenomena
Data Collection	Conduct surveys and collect data	Conduct research on economic phenomena, including collecting and analyzing data	Collect and analyze economic data to identify trends and make forecasts
Data Analysis	Analyze data using mathematical models, statistical tools, and software	Analyzing economic trends and making forecasts	Collect and analyze economic data to identify trends and make forecasts
Trend Forecasting	Interpret and forecast market trends	Analyzing economic trends and making forecasts	Collect and analyze economic data to identify trends and make forecasts
Advisory Roles	Advise businesses, governments, and individuals on economic topics	Providing advice to businesses, government agencies, and individuals on economic policy and strategy	Advise on economic policy, strategy, and planning
Report Preparation	Present research in reports, tables, and charts for academic journals, government publications, and other media	Preparing reports and publications based on research findings	Prepare economic reports and papers
Policy Recommendations	Recommend solutions to economic problems	Formulating theories, policies, and strategies for economic development and	Formulate recommendations for economic development and growth

		monitoring their implementation	
Policy Evaluation		Evaluating the impact of economic policies and proposals	Evaluate the effectiveness of economic policies and programs

8.2 Descriptions of Varieties of Capitalism Classifications

The three main Classifications used by this theory and its iterations are (Hall and Sosckice, 2001):

a. Coordinated Market Economies (CMEs), e.g. Germany or Sweden:

   i. Collaboration and Coordination: In CMEs, businesses, labor unions, and the government work closely together to coordinate their activities. This collaboration aims to maintain stability and long-term growth.
   ii. Strong Labor Unions: Labor unions play a significant role in negotiating wages and working conditions, often resulting in higher job security and benefits for workers.
   iii. Skill Development: There is a strong emphasis on skill development and vocational training. Companies invest in their employees, leading to a highly skilled workforce.

b. Liberal Market Economies (LMEs), e.g. Ireland or the UK:

   i. Market-Driven: LMEs rely heavily on market mechanisms to allocate resources and determine prices. Businesses compete more aggressively, and there is less government intervention.

   ii. Flexible Labor Markets: Employment relationships tend to be more flexible, with weaker labor unions and less job security. Companies can hire and fire workers more easily based on market needs.

   iii. Innovation and Entrepreneurship: There is a strong focus on innovation and entrepreneurship, with an emphasis on short-term financial performance and shareholder value.

c. Mixed Market Economies (MMEs), e.g. France or Italy:

i. Hybrid Approach: MMEs combine elements of both CMEs and LMEs. They have features of coordination and collaboration, but also allow for significant market competition.

ii. Varied Government Role: The role of the government in the economy can vary widely, providing support and regulation in some sectors while allowing free-market mechanisms in others.

iii. Balanced Labor Markets: Labor markets in MMEs may offer more protection than in LMEs but are not as rigid as in CMEs. This balance can lead to moderate job security and flexibility.

8.3 Python Code used for structuring data

The following Pyhton script was used to calculate the average values of all the variables per ISCO 3-digit code per country per year:

Example for the Austrian 2015 sample

```
import pandas as pd
import numpy as np

# Define the path to the original CSV file
file_path = '/Users/andreasdemetriou/Library/Mobile
Documents/com~apple~CloudDocs/Documents/UCY Master Econ Analysis/Econ 699 -
Dissertation/Data/ELFS/ELFS Austria 2015-20/AT2015_y.csv'

# Load the CSV file
data = pd.read_csv(file_path, low_memory=False)

# Select only numeric columns for processing
numeric_data = data.select_dtypes(include=[np.number])

# Check if 'ISCO3D' is available and numeric for grouping
if 'ISCO3D' in numeric_data.columns:
    averages = numeric_data.groupby('ISCO3D').mean()

    # Build the new filename
    # Split the original path by '/' and pick the last part (the filename)
    original_filename = file_path.split('/')[-1]
    # Split the filename by '.' and insert 'averaged' before the extension
    new_filename = original_filename.split('.')[0] + '_averaged.csv'

    # Save the averages to a new CSV file
    averages.to_csv(
        '/Users/andreasdemetriou/Library/Mobile
Documents/com~apple~CloudDocs/Documents/UCY Master Econ Analysis/Econ 699 -
Dissertation/Data/ELFS/' + new_filename)
else:
```

```
    print("ISCO3D is not a numeric column or not found in the dataset.")
    # Optionally, handle the situation differently if ISCO3D isn't
available or numeric
```

Python Code for measuring the number of respondents per each ELFS dataset (example from Austria):

```
import pandas as pd

# Define the file paths based on your specified folder for Austria
base_path = '/Users/andreasdemetriou/Library/Mobile
Documents/com~apple~CloudDocs/Documents/UCY Master Econ Analysis/Econ 699 -
Dissertation/Data/ELFS/ELFS 3D/ELFS Austria 2015-20/'
file_paths = [
    f'{base_path}AT2015_y.csv',
    f'{base_path}AT2016_y.csv',
    f'{base_path}AT2017_y.csv',
    f'{base_path}AT2018_y.csv',
    f'{base_path}AT2019_y.csv',
    f'{base_path}AT2020_y.csv'
]

# Initialize an empty DataFrame to collect the results
combined_data = pd.DataFrame()

# Process each file with low_memory=False to avoid DtypeWarning
for file in file_paths:
    year = file.split('/')[-1][2:6]  # Correct extraction of the full year
from filename
    print(f'Processing file for the year: {year}')
    data = pd.read_csv(file, low_memory=False)  # Load data with low_memory
set to False
    if 'ISCO3D' in data.columns:
        data = data[['ISCO3D']]  # Select only the ISCO3D column
        data['Year'] = year  # Assign year
        combined_data = pd.concat([combined_data, data])  # Append to the
combined dataframe

# Correctly group by 'ISCO3D' and 'Year' and count the occurrences
grouped_data = combined_data.groupby(['ISCO3D',
'Year']).size().reset_index(name='Count')

# Create the wide format using pivot
wide_format = grouped_data.pivot(index='ISCO3D', columns='Year',
values='Count').reset_index()
wide_format.fillna(0, inplace=True)  # Replace NaN with 0

# Calculate the total count of respondents for each year and add as a new
row
totals = wide_format.iloc[:, 1:].sum().rename('Total')
totals = pd.DataFrame(totals).T
totals['ISCO3D'] = 'Total'
totals = totals[['ISCO3D'] + [col for col in totals.columns if col !=
'ISCO3D']]

wide_format = pd.concat([wide_format, totals], ignore_index=True)

# Save to CSV files
long_format_path = f'{base_path}ELFS_Austria_2015_2020_long.csv'
wide_format_path = f'{base_path}ELFS_Austria_2015_2020_wide.csv'
```

```
grouped_data.to_csv(long_format_path, index=False)
print(f'Long format data saved to: {long_format_path}')
wide_format.to_csv(wide_format_path, index=False)
print(f'Wide format data saved to: {wide_format_path}')
```

Python code for merging the ELFS the datasets measuring the number of respondents:

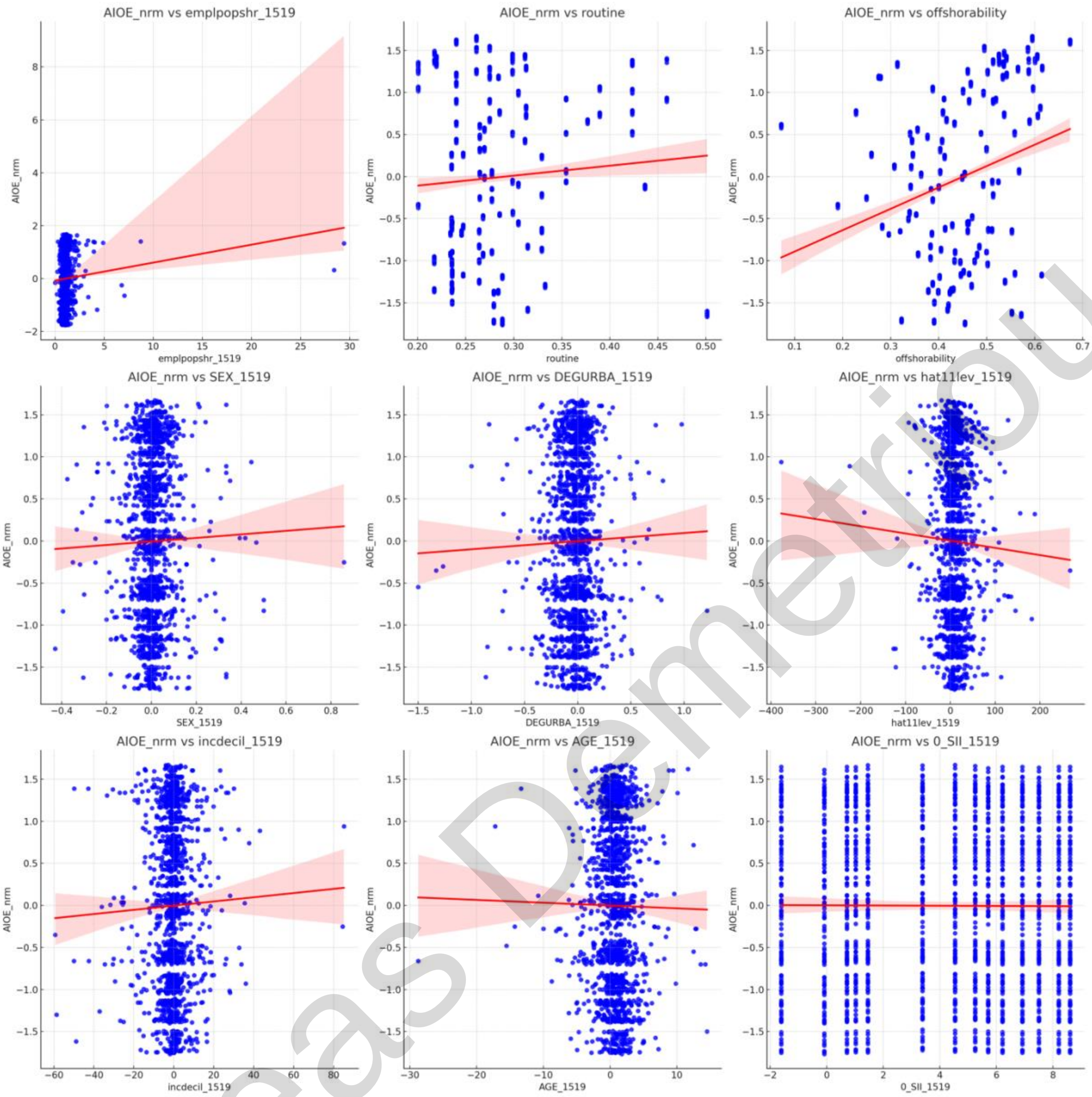
```
import pandas as pd

# Define the file paths for wide format files
wide_files = [
    'path/to/ELFS_Austria_2015_2020_wide.csv',
    'path/to/ELFS_Belgium_2015_2020_wide.csv',
    'path/to/ELFS_Denmark_2015_2020_wide.csv',
    'path/to/ELFS_Finland_2015_2020_wide.csv',
    'path/to/ELFS_France_2015_2020_wide.csv'
]

# Load and merge all wide format files
wide_dfs = [pd.read_csv(file, index_col='ISCO3D') for file in wide_files]
combined_wide_df = pd.concat(wide_dfs, axis=1).fillna(0)  # Fill NaN with 0
to avoid data loss

# Save the combined wide format data to a new CSV file
combined_wide_df.to_csv('ELFS_Combined_2015_2020_wide.csv')

# Output the paths where the files would be saved
print('Combined long format file saved as:
ELFS_Combined_2015_2020_long.csv')
print('Combined wide format file saved as:
ELFS_Combined_2015_2020_wide.csv')
```


AIOE_nrm vs emplpopshr_1519
emplpopshr_1519
AIOE_nrm vs routine
routine
AIOE_nrm vs offshorability
offshorability
AIOE_nrm vs SEX_1519
SEX_1519
AIOE_nrm vs DEGURBA_1519
DEGURBA_1519
AIOE_nrm vs hat11lev_1519
hat11lev_1519
AIOE_nrm vs incdecil_1519
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AIOE_nrm vs 0_SII_1519
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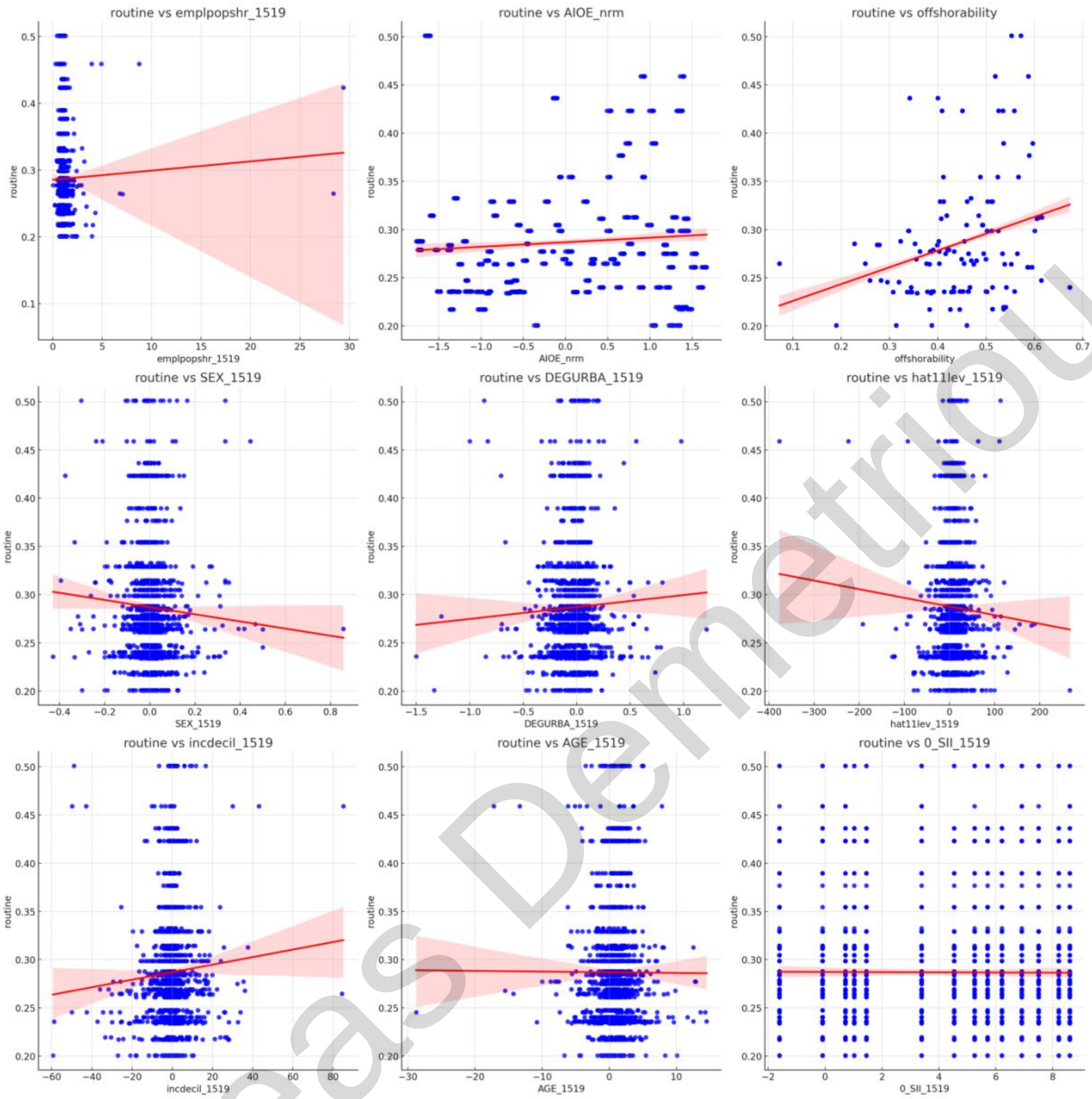
AIOE_nrm


routine vs emplpopshr_1519
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routine
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routine vs SEX_1519
routine
SEX_1519
routine vs DEGURBA_1519
routine
DEGURBA_1519
routine vs hat11lev_1519
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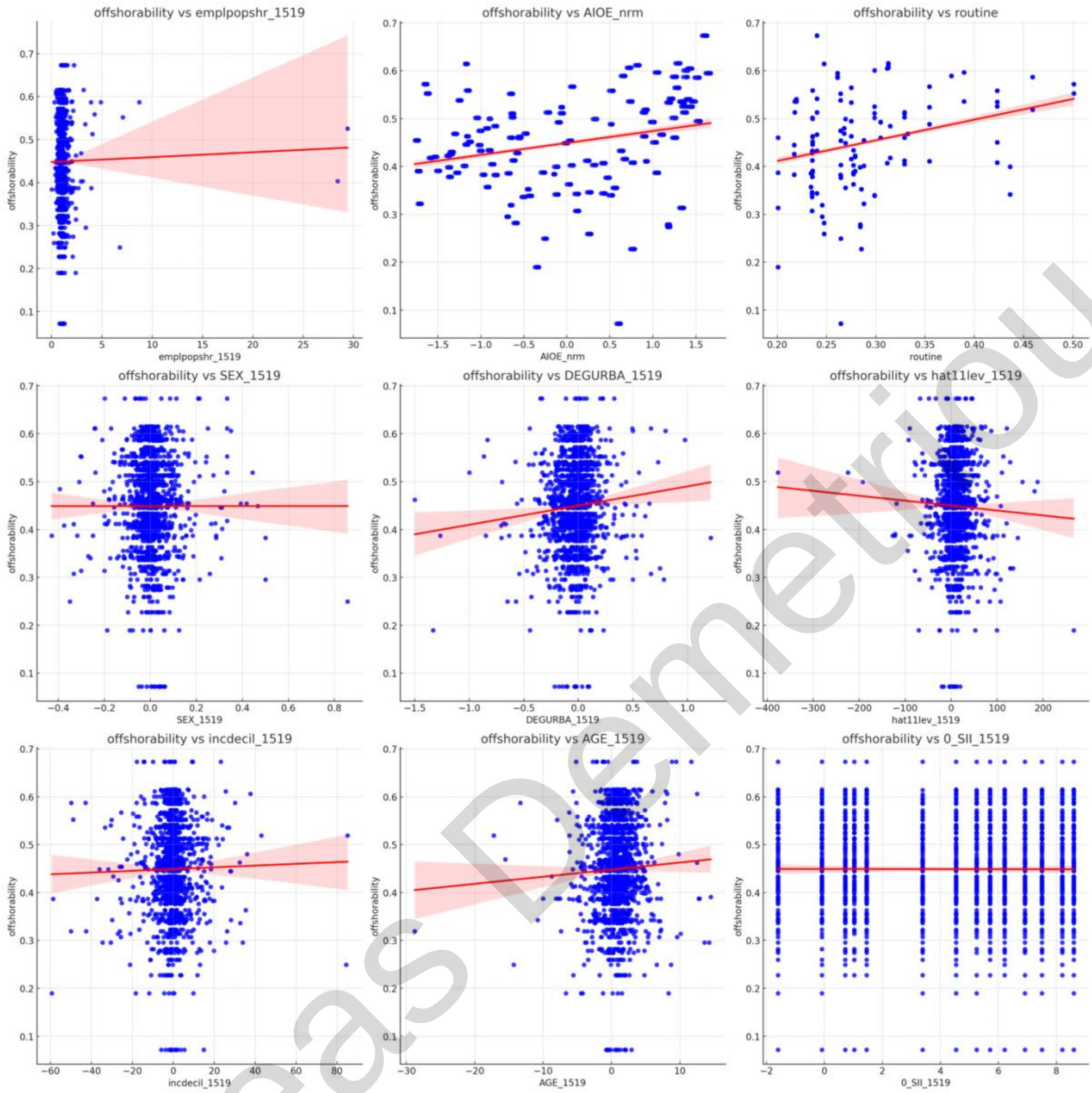
routine
0_SII_1519



8.4 Regression Results

8.4.1 Main results

Section:	(5.3.1)	(5.3.2)	(5.3.3)	(5.3.4)	(5.3.5)	(5.3.6)	(5.3.7)
AIOE	0.072**	0.073**	0.077**	0.151*	0.077**	0.077**	0.077**
	(0.025)	(0.023)	(0.025)	(0.065)	(0.025)	(0.025)	(0.025)
Routine		0.347	0.311	0.318	0.278	0.309	0.309
		(0.568)	(0.631)	(0.633)	(0.617)	(0.628)	(0.628)

Offshorability	-0.115	-0.134	-0.141	-0.135	-0.139	-0.135
	(0.146)	(0.153)	(0.154)	(0.152)	(0.154)	(0.153)
Change in Gender		0.180	0.222	0.216	0.188	0.194
		(0.538)	(0.528)	(0.523)	(0.540)	(0.539)
Change in household urbanization		0.173	0.175	0.182	0.149	0.155
		(0.168)	(0.169)	(0.188)	(0.170)	(0.172)
Change in higher educ level		-0.000	-0.000	-0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Change Income		0.005	0.005	0.008	0.005	0.005
		(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Change in Age		-0.015	-0.015	-0.019	-0.014	-0.015
		(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Innovation Interaction			-0.018			
			(0.010)			
Austria				0.000		
				(.)		
Belgium				-0.254		
				(0.238)		
Denmark				-0.223		
				(0.233)		
Finland				-0.274		
				(0.228)		
France				-0.310		
				(0.239)		
Germany				-0.331		
				(0.247)		
Greece				-0.265		
				(0.226)		

Ireland					0.208		
					(0.367)		
Italy					-0.290		
					(0.237)		
Luxembourg					-0.257		
					(0.247)		
Netherlands					-0.291		
					(0.217)		
Portugal					-0.240		
					(0.226)		
Spain					-0.172		
					(0.238)		
UK					-0.330		
					(0.247)		
CME						0.000	
						(.)	
MME						0.107	
						(0.100)	
LME						-0.026	
_cons	1.084***	1.036***	1.080***	1.080***	1.308***	1.069***	1.007***
	(0.025)	(0.163)	(0.194)	(0.194)	(0.370)	(0.220)	(0.267)
N	1764	1764	1616	1616	1616	1616	1616
r2	0.005	0.005	0.010	0.013	0.027	0.012	0.011

8.4.2 Result for the normalized employment share change

	(5.3.1)	**(5.3.2)**	**(5.3.3)**	**(5.3.4)**	**(5.3.5)**
aioe_nrm	0.105***	0.109***	0.104***	0.180***	0.104***
	-0.022	-0.022	-0.023	-0.035	-0.023
routine		-1.395***	-1.261***	-1.252***	-1.265***
		-0.391	-0.398	-0.399	-0.399

offshora	0.172	0.074	0.068	0.074
	-0.236	-0.244	-0.244	-0.245
sex_1519		0.634**	0.676**	0.649*
		-0.322	-0.319	-0.331
degurba_		0.025	0.027	0.018
		-0.134	-0.134	-0.141
hat11l~_		-0.001	-0.001	-0.001
		-0.001	-0.001	-0.001
incdec~_		0.002	0.002	0.002
		-0.003	-0.003	-0.003
age_1519		-0.01	-0.009	-0.011
		-0.01	-0.01	-0.01
c._sii_1			-0.018***	
-0.007				
1.cc_id				0
				(.)
2.cc_id				0
-0.131				
3.cc_id				0.013
-0.128				
4.cc_id				-0.024
-0.128				
5.cc_id				-0.001
-0.13				
6.cc_id				0.003
-0.132				
7.cc_id				0.033
-0.128				

8.cc_id					0.089
-0.123					
9.cc_id					0.007
-0.132					
10.cc_id					0.021
-0.129					
11.cc_id					0.02
-0.129					
12.cc_id					0.024
-0.127					
13.cc_id					0.002
-0.134					
15.cc_id					-0.006
-0.134					
_cons	0	0.324***	0.347**	0.346**	0.336*
	-0.023	-0.123	-0.136	-0.137	-0.179
--------	-------------------	-------------	----------------	----------------	----------------
N	1781	1781	1631	1631	1631
r2	0.0111486	0.0186528	0.0223704	0.0259308	0.0229775
--------	-------------------	-------------	----------------	----------------	----------------
Standard	ors in parentheses				
*** p<0.1,**	p<0.05, *** p<0.01				