AI and Labor Market Matching Efficiency

Investigating the relationship between AI adoption and matching efficiency in the European labor market

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Abstract:

The recent developments in artificial intelligence are bound to change established work processes and in turn labor markets. One dimension – which AI impacts – is the labor market matching efficiency. The net effect of increased AI usage on the matching quality is ambiguous, as it affects several dimensions of the matching process. Using data from Eurostat, OECD and other national statistical bureaus, the relationship between AI and matching efficiency in Europe is estimated. Applying the Beveridge curve to measure matching efficiency, no relationship between increased AI usage and matching efficiency is found. If anything, using a broader measurement than unemployment – labor market slack – AI is correlated with improved matching efficiency. Findings also show industry heterogeneity, where job vacancies are impacted differently by AI depending on the industry. Regardless, the aggregated job vacancy is not correlated with increased AI usage. As such, findings suggest that net gains made from AI adoption are unlikely to come at the expense of a worse matching quality in Europe.

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1. Introduction

Disruptive technologies occur rarely; when they do, major structural changes in the economy usually follow. This economic dynamism is well documented. For instance, Schumpeter's concept of creative destruction describes the process of displacing established technologies and sectors through innovation. Schumpeterian innovation aims to replace old technologies, altering the economic context and, subsequently, its organization. This presents the 'paradox' of creative destruction – some will be worse off due to the disruption, both in the short and long term (McCraw, 2007).

In a period where artificial intelligence aims to reshape entire industries, the concept of creative destruction has never been more relevant. Previously established economic organization will be overturned, causing both gains and losses within society. Therefore, it is interesting to attempt estimating AI's impact on labor market conditions. Since the economic structure likely will change, how will labor be impacted? At first glance, the impact of AI seems to be somewhat ambiguous; it is increasingly used in labor market matching, which could improve the search process of finding people with the right skills (Broecke 2023). On the other hand, technological development has been stated as a probable cause of skills shortage (Gidehag, 2024).

While AI's impact on employment within Europe has previously been investigated by other studies, such as Guarascio et al. (2025), there is a significant gap in research regarding its effect on labor market matching efficiency. Matching efficiency is a more nuanced and broader measurement, as the labor market is measured in more dimensions. Furthermore, previously mentioned literature has focused on the 2010s, meaning that they are estimating a widely different AI landscape. This thesis addresses these gaps by investigating whether AI improves matching efficiency in the current European labor market and if so, how it might reshape broader labor market outcomes. To quantify the matching efficiency, the Beveridge curve is used – which captures the negative relationship between unemployment and job vacancies. Furthermore, the thesis investigates heterogeneity in labor market matching across industries to determine industry differences of the impact of AI.

Based on what has been stated above, the posed research question is the following: how does AI impact matching efficiency in Europe and its industries? The main research question leads to the following hypotheses: AI has an ambiguous impact on matching efficiency, with heterogenous effects across industries. This will be further explained in the theoretical framework (Section 3.3.).

To answer the research question, an OLS panel data regression with unit fixed and time fixed effects is used. The model uses European countries and regions as units over the years 2021, 2023 and 2024. Our results show no clear correlation between AI usage and matching efficiency as the effect of AI on both unemployment and job vacancies is statistically insignificant. This indicates that the effect is ambiguous and that given the right context, AI adoption is unlikely to result in a worsened matching quality. If anything, our analysis suggests that increased AI usage is more likely to lead to improved matching efficiency, since the results show a negative correlation between AI adoption and labor market slack.

From the findings in this report, it cannot be stated that the vacancy rate is affected by AI, but the results suggest that there is heterogeneity between industries – indicating that vacancy rates in AI-exposed industries may be more affected than in less exposed industries. However, the analysis is limited due to shortcomings of data, leading to a lack of causal inference tools and omitted variable bias. Therefore, results must be interpreted with caution.

The structure of the thesis will be the following: initially, previous literature and studies on the topic are presented in the literature review (2), which is then followed by the theoretical framework (3), where key definitions and theories for describing labor market matching and AI are presented. Next, the data (4) used will be described and limitations discussed. Afterwards, the thesis will delve into the model specification (5). Lastly, results from the different regression analyses will be shown and discussed in the results (6) and discussion (7) sections, followed by the conclusion (8).

2. Literature review

Artificial Intelligence (AI) plays an increasingly disruptive role in modern labor markets by enabling computers and machines to simulate human intelligence. It engages with different analytical and algorithmic aspects of problems by using computational models. Applications using AI can automate processes, acting independently. What most researchers refer to as AI in recent studies is the so-called generative AI; deep learning models that can create original content. Machine-learning and other types of automations have been around for some time, although recent strides in generative artificial intelligence are new (Mahato, 2022). The new wave of AI from the 2010s onwards will have impacts on the structural dynamics of the economy.

The diffusion of AI across different fields has profoundly evolved and overturned sectoral structures. AI adoption success within companies is strongly correlated with digital skills, R&D intensity and enterprise size. Utilization is also common in healthcare, where it has become a diagnostic tool for illnesses such as cancer. Although AI provides users with cost-effectiveness and reliability, it could be a source of major work loss (Mahato, 2022).

Recent literature suggests that approximately a third of all professions are entirely exposed to generative AI. Since its release in November of 2022, ChatGPT rapidly amassed over a million registered users – faster than even TikTok and Instagram. As such, there has been a rapid rise in AI usage, potentially transforming labor market dynamics. Because AI is substitutive for human labor, the implications could be large disruptions in specific market segments. The impact is diverse and complex – hard to estimate. This is due to the ambiguity of impacts; AI has the potential to both complement and substitute labor. As such, the effects on the labor market are two-way. The study only reflects potential labor market implications and not realized ones; as such, the estimate of exposed professions is speculative as of now (Zarifhonarvar, 2023).

In an OECD (Causa et al., 2025) report, it is stated that a plethora of professions are in short supply. The organization also points out that many professions are at risk due to the rapid advances in AI, causing a change in both sought-after skills and labor. In another report, the benefits of AI in labor matching are explained. Apart from simply being cost-efficient, the introduction of AI may also improve the quality of matching as well as the experience for the applicants. Additionally, the introduction of AI may serve to reduce human bias in selection, making sure that the most suitable applicant is employed. For instance, use of AI for job descriptions could induce a higher diversity of applicants (Broecke, 2023).

Furthermore, mismatches in the labor market have great economic implications. For instance, it has been named as an implicit driver for the lower economic growth experienced in the United Kingdoms. After the Financial Crisis in 2008, growth in the UK fell below the previous trend. By reducing regional mismatches within the UK, studied through job vacancies, growth trends return to their pre-crisis levels (Turell et al., 2018). Moreover, the movement in matching efficiency depends on the degree of heterogeneity in the labor market. Matching efficiency declines substantially when the average characteristics of the unemployed deteriorate, or when differences in labor market conditions increase between sectors (Barnichon & Figura, 2015). As such, if there are large differences between workers, the matching efficiency will likely worsen. As Acemoglu and Loebbing (2024) mention, the increased usage of AI leads to market polarization, increasing differences between workers. As such, it is interesting to investigate what the effect of AI would be on labor market matching.

A usual approach to measure matching efficiency is through the so-called Beveridge curve. The Beveridge curve shows the negative relationship between unemployment and job vacancies. Shifts suggest changes in matching efficiency while movements along the curve simply suggest cyclical variation (Sveriges Riksbank, 2024). As such, when events such as Covid-19 occur, it is interesting to analyze shifts in the Beveridge curve to explain the changing matching efficiency. While studies have been conducted to see the impact of Covid-19 on overall matching efficiency through the Beveridge curve, such studies do not currently exist for AI.

Focusing on Europe, a new study by Guarascio et al. (2025) investigates AI and employment patterns across the European regions using data from the 2010s. The authors conclude that their findings suggest great uncertainty regarding the impact of AI on labor markets; it is highly heterogenous across different regions, potentially deepening regional inequalities. Some sectors and activities may prove more apt to adopt the novel technology, such as the high-tech sectors, potentially complementing labor instead of substituting for it. Consequently, impacts for each sector and economy will have to be investigated individually.

In a recent study, Wiles and Horton (2025) analyze the impact that generative AI has on labor market matching by running an experiment on an online labor market. The effect is estimated by offering randomly selected would-be employers an AI-written first draft of their job posts. They find that the AI service led to a substantial increase in in the number of job posts and is considerably time-saving for the employers who use it. However, they observed no net increase in matches despite the increase in the job posts and that the marginal jobs induced by the treatment were less likely to hire. The AI assistance made the job posts less informative about the employer's needs which led to jobseekers spending time applying for jobs they otherwise would not have. Their results show that the value of wasted, and time saved suggest that the per job post loss to jobseekers is six times larger than the increase to employer welfare and that the AI tool had a negative impact on labor market matching efficiency.

As can be seen from the research mentioned, the field of AI and labor markets is largely understudied. Research in the field is often speculative as AI developments are difficult to investigate due to the recency. Furthermore, before the launch of ChatGPT, AI was not as debated and investigated. It is only due to recent disruption in the field that research has increased exponentially. Consequently, there are several literature gaps in the field – not exclusively limited to AI and labor markets. There are also concerns regarding the age of data used in the different studies. For instance, Guarascio et al. (2025) use data from the 2010s to investigate the relationship between employment and AI in Europe. This data is prior to recent developments, which means that the estimated relationship may not be the same today as it was then.

This thesis contributes to the growing research of artificial intelligence and its impact on the labor market by looking at recent data in the European labor market. Unlike many previous studies, our report looks at timely data from the early 2020s which enables us to capture the recent boom in AI. These years are crucial when investigating the connection between AI and the labor market, since artificial intelligence has changed with the introduction of smarter generative AI. Furthermore, we expand on the subject by applying quantitative methods to real world data, moving beyond conceptual frameworks and economic theories. This approach enables the investigation of the relationship between AI and various factors in the labor market.

While previous studies on AI and the labor market exist, this report offers a distinct contribution by focusing specifically on the relationship between AI and labor market matching efficiency on a macro-level. This makes it possible to not only capture the negative effects that are found by Wiles and Horton (2025), but also the potential positive effects that AI could have on matching efficiency. As a result, the net effect of AI adoption on matching efficiency can be estimated, rather than focusing on one-sided impacts.

3. Theoretical Framework

3.1. Artificial Intelligence and Technological Advancement.

3.1.1. Artificial Intelligence

Different industries are exposed to AI in different degrees and ways. Felten et al. (2021) has produced a measurement of AI exposure at the industry level. Initially the authors relate ten AI applications (e.g., image generation, language modeling and speech recognition) to 52 O*NET occupational abilities (e.g., mathematical reasoning, written comprehension, speech recognition) generating an index value between 0 and 1 for AI's ability to perform a task. The formula is presented below, where x_{ij} represents the relevance of AI application i to occupational ability j:

$$A_{ij} = \sum_{i=1}^{10} x_{ij}$$

The index of the AI's ability level is then related to each occupation, where each k occupational AI exposure (AIOE) is calculated by the following equation:

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

The authors weigh the importance of each ability based on prevalence (L) and importance (k) within each occupation. The professions are then aggregated for each industry based on their relative weight, and an AI industry exposure (AIIE) measurement is calculated. Naturally, some sectors are more exposed to AI than others; financial and accounting industries rank quite highly, while construction and support activities rank low (see table below). This reveals a clear heterogeneity across sectors – some will be more affected by AI than others. As Guarascio et al. (2025) points out, the ability to complement AI rather than substitute also vary extensively across professions and industries. For instance, high-tech sectors are generally more apt to complement existing labor. Therefore, heterogeneity for each profession's AI outcome exists; will it worsen or improve labor market conditions?

Table 1. Most and least exposed industries.

10 Most Exposed Industries	AIIE
Securities, Commodity Contracts, and Other Financial Investments and Related Activities	2,219
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	2,216
Insurance and Employee Benefit Funds	2,180
Legal Services	2,157
Agencies, Brokerages, and Other Insurance Related Activities	2,121
Nondepository Credit Intermediation	2,113
Other Investment Pools and Funds	2,070
Insurance Carriers	2,059
Software Publishers	1,966
Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	1,911
10 Least Exposed Industries	**AIIE**
Support Activities for Crop Production	-2,165
Services to Buildings and Dwellings	-1,999
Foundation, Structure, and Building Exterior Contractors	-1,757
Animal Slaughtering and Processing	-1,663
Building Finishing Contractors	-1,603
Warehousing and Storage	-1,591
Fiber, Yarn, and Thread Mills	-1,588
Support Activities for Rail Transportation	-1,475
Sawmills and Wood Preservation	-1,421
Support Activities for Water Transportation	-1,411

Source: (Felten, E., et al. (2021). AI Occupational Exposure [Dataset]. (Retrieved from https://github.com/AIOE-Data/AIOE)

3.1.2. Diffusion of Innovation

Adoption of innovations does not occur overnight; it is a gradual process. The diffusion of innovation theory described by Roger Everett divides individuals into different adopter categories. Everett stresses that at first there are only a few open to adopting an innovation, and as time progresses and word spreads of the innovation, adoption speed will increase. This results in the S-shaped curve for the cumulative adoption of innovation. Each category of adopters is divided into a normal distribution. This means that the categories in the middle of the distribution will be of a greater proportion; therefore, the diffusion will first have slow growth, followed by a sharp increase which then tapers off as the cumulative adoption rate reaches a hundred percent (Kaminsky, 2011).

Early adopters are characterized by being affluent and wanting to reshape the current competitive structure in their respective industries. Additionally, they are less risk averse due to having more resources; the early adopters can afford failure (Kaminsky, 2011). The implications are that larger companies and richer countries are more prone to adopting innovations faster due to greater resources (Maloney & Cirera, 2017).

According to OECD (Calvino & Fontanelli 2023), the diffusion theory also describes general AI adoption well; larger and productive firms are more likely to adopt AI. At the same time, AI gains are captured by wealthier nations, potentially widening the pre-existing gap between low- and high-income countries. (Fan & Qiang, 2024).

There is also a relationship between AI adoption and education level; individuals with a higher education level show a higher level of trust towards AI-powered recommendations (Biswas & Murray, 2024). This contributes to existing economic literature, where the education level determines the degree of advanced technologies used (Gottfries, 2013). Therefore, countries with higher education levels would be more prone to adopt AI; the exposure to AI should be higher.

3.2. Labor Market Matching

Labor market matching refers to how efficiently supply and demand for labor meet. High matching efficiency facilitates the process of firms finding the right workers and workers process of finding suitable jobs. This leads to reduced periods of unemployment and thus lower equilibrium unemployment. In turn, this will have a positive impact on potential employment and output in the economy. Conversely, poor matching efficiency leads to longer periods of unemployment and higher equilibrium unemployment, and thus lower potential employment and output. (Häkkinen Skans & Wasén, 2025)

The growing skills mismatch, partly driven by AI, has not been adequately addressed by aligning conventional training programs with changing demands on the labor market. By recognizing AI's complementarity in the workplace, there is an opportunity to improve the reskilling process. Some European countries have attempted to follow this approach through different policies. For instance, the Netherlands has offered grants and guidance for training workers above 45 in the ICT sectors (Stephany & Teutloff, 2023).

The matching efficiency cannot be measured directly, but with various estimates and indicators it can be assessed. This section introduces a widely used method for measuring labor market matching – the Beveridge Curve – which will be used extensively throughout the report.

3.2.1. The Beveridge Curve

The Beveridge curve represents the negative relationship between the unemployment rate and job vacancy rate; as job openings increase, unemployment decreases. Movements along the curve reflect changes in labor market tightness. In a tight labor market – where supply for labor is low, and demand high– there is a low unemployment rate combined with a high vacancy rate. In the case of a slack labor market, it is the opposite. In this scenario, unemployment is high and there are few vacancies with high labor supply and low labor demand. As such, the tight labor market is associated with upward pressure on wages while the slack labor market is associated with downward pressure (Eurostat, 2024).

The Beveridge curve also shows changes in the matching efficiency between labor demand and supply, which causes the curve to shift. Improved matching efficiency means that it is easier for unemployed people to find a job at a given vacancy rate; this changing labor market condition is shown by an inward shift in the Beveridge curve. Conversely, an outward shift of the curve is related to a decline in matching efficiency. This is potentially due to skill mismatches or other types of frictions on the labor market (Eurostat, 2024).

Artificial intelligence can cause labor shortages and unemployment simultaneously. Emerging technologies have the capability to substitute the traditional labor requirements, while at the same time providing new possibilities with job creation. This ambiguity means that the total effect on the labor market is uncertain (Stephany & Teutloff, 2023); that the impact on the Beveridge curve is not known.

3.2.2. Unemployment

As stated, unemployment is one of the two dimensions of the Beveridge curve. Unemployment is a source of poverty and inequality. High unemployment means that fewer individuals are working – which is a waste of resources. In other words, it means that production is lower than it could be. Unemployment is normally measured as a percentage of the labor force, which consists of employed and unemployed people. An individual must actively be searching for or waiting to start a job to count as unemployed. People who do not work or actively seek work are counted as outside of the labor force. These three states – employed, unemployed, and outside the labor force – are the key stock variables describing the state of the labor market, and there are constant flows of workers between these states. (Gottfries, 2013)

Wages are a key factor influencing the level of unemployment. The average unemployment rate over a business cycle is often called the *natural* rate of unemployment, or the *long-run equilibrium*. According to the *wage-setting equation,* when unemployment is below the natural rate, firms face higher turnover risks and desire to set wages above the average wage level to retain their workers. Conversely, when unemployment is above this rate, firms desire to set wages below the average wage level. When unemployment is at an equilibrium, no firms have incentives to change their relative wage – the relative wage is unity between firms. However, wages are not always fully determined by the market. In many countries, minimum wages are set by the government or in union contracts. Minimum wages may contribute to increased unemployment among low skilled workers, and this problem worsens by skilled-bias technical change, which increases the demand for highly skilled workers. (Gottfries, 2013)

3.2.3. Job Vacancies

The second dimension of the Beveridge curve – job vacancies – refers to the number of available jobs that are open for applications. Eurostat (n.d.) defines a job vacancy as "a paid post that is newly created, or about to become vacant". Additionally, employers must actively be taking steps to find a suitable candidate from outside the enterprise and intend to fill the post immediately or within a specific period of time.

Donker van Heel (2015) distinguishes between two different concepts of job vacancies – the concept of unmet demand and the concept of job matching. The concept of unmet demand represents the demand side of the labor market and is based on macro-level economic analysis. It looks at job vacancies as unoccupied jobs that are immediately available and needed to resume or maintain production. The concept of job matching is based on the search behavior of both parties and has more of a micro-level perspective. This concept views job vacancies as a potential match between employers and job seekers. It includes both occupied and unoccupied posts, and vacancies do not need to be actively recruited for.

As illustrated in the Beveridge curve, economic theory suggests a negative relationship between unemployment and job vacancies. A higher number of job openings typically indicates increased labor demand, meaning there are more jobs to apply to for unemployed people. This, in turn, facilitates the process of finding a job and reduces the time of unemployment. (Gottfries, 2013)

3.2.4. The European Labor Market

Recently, the EU labor market has been surprisingly resilient, with unemployment at an all-time low. Simultaneously, the labor market is experiencing a strong growth in employment. This is despite the difficult economical contexts and more hostile geopolitical climate. This is due to the existing skill and labor shortages within the EU, which has caused companies to retain their employees despite the economic downturn. It is highly doubtful however, whether this trend will continue in the medium- to long-term (European Commission, n.d.).

In the labor market report the year prior, Mînzatu claims that the EU labor market faces four major challenges. Firstly, skill- and labor shortages are a critical concern, not only in sectors that are essential for green and digital transformations, but also in construction and health care to name a few. Additionally, the EU faces lower real wages for middle- and low-income households. The lasting slow growth in production, innovations and general investments is also a major concern for the EU labor market, as work opportunities may not be created fast enough. Lastly, there has been a nominal decline in the income allotted to the worker as compensation for their labor over the last two decades (European Commission, 2024).

Furthermore, the progress made in automation, robotics and artificial intelligence are changing current labor market dynamics in Europe. Contemporary literature claims there is a greater technologization of the work processes than ever before. For instance, from 2017 to 2022, there was a 12% increase in the industrial and service robots per 1,000 workers. This process has also been sped up further because of the Covid-19 pandemic. Future developments, mainly in the form of AI, has even more disruptive effects. The rapid diffusion of AI – particularly generative AI – is the root cause of the disruption. Since it transforms work processes tremendously, the quick diffusion leads to immediate disruptions on the European labor market (Molek, 2024).

The most used AI technology by companies in Europe is different types of AI process automation software. The technology is meant to assist decision making and streamline processes. It is used by approximately 4% of all companies in the EU. There is also usage of AI for text mining – AI is used to analyze the written language and provide meaningful information. Circa 3.5% of companies use this technology. The same percentage of companies also use machine learning for data analysis. These are the three largest types of formal usage of AI among companies within the EU (Molek, 2024).

3.3. AI and the Beveridge Curve: A Conceptual Framework

What impact could AI usage have on the Beveridge Curve? As the Beveridge Curve is on a two-dimensional plane, it can effectively shift in 4 directions. Shifting upwards and downwards affects job vacancies; if the Beveridge curve shifts upwards, there will be more vacancies at a given unemployment rate. Shifting sideways will instead affect unemployment. A shift to the right from the origin corresponds to a higher unemployment rate at a given job vacancy rate. Any shift outwards from the origin corresponds to a deterioration of the matching efficiencies. Sometimes, these changes may be simply cyclical and return to normal in the long run (Sveriges Riksbank, 2025). Presented beneath is the evolution of Sweden's changing Beveridge Curve (Figure 1). As can be seen, the Beveridge curve is not static, it shifts and changes frequently as the conditions for labor market matching evolves.

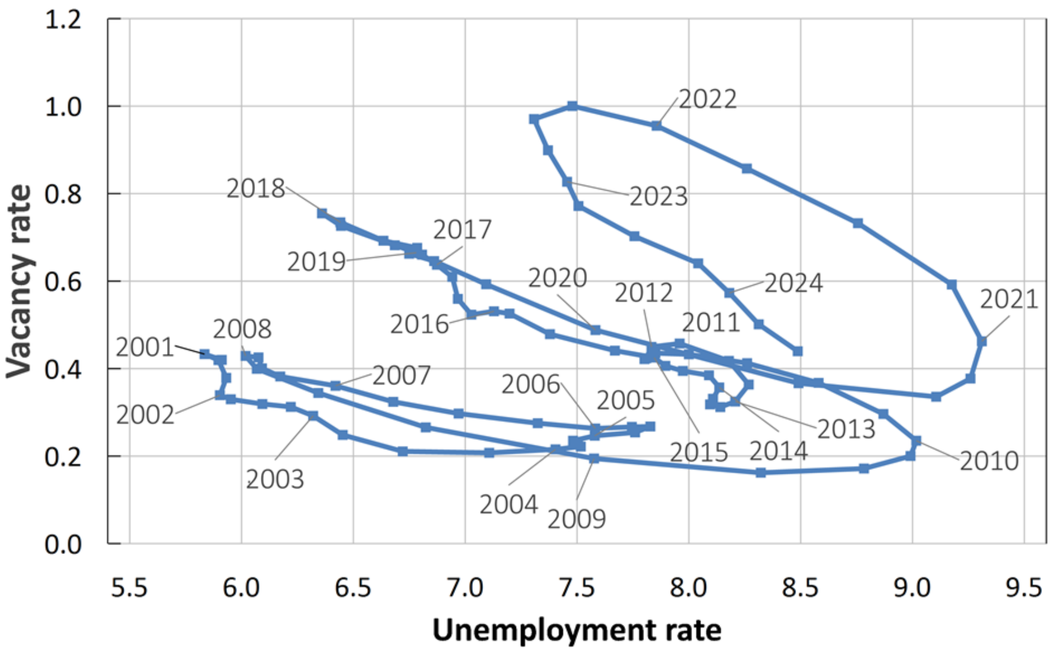

Figure 1. Sweden's Beveridge Curve 2001-2024. Source: (Riksbank (2025), *Beveridge Curve 2001-2024*. Sveriges Riksbank, https://www.riksbank.se/en-gb/press-and-published/publications/economic-commentaries/labour-market-matching-in-sweden/the-beveridge-curve--an-illustration-of-matching-efficiency/)

The disruptive nature of AI may uproot the normal labor market matching efficiencies or shift them altogether. As such, what will be investigated is whether there is an economic and significant shift in the Beveridge curve from increasing AI-usage. If AI has a negative relationship with one of the two dimensions, an increase in AI usage would shift the curve towards the origin, either horizontally or vertically depending on the dimension. In this scenario, AI would improve labor market efficiencies. If the relationship is positive, the opposite occurs – AI has a negative impact on market efficiencies. If job vacancies move in one direction – and unemployment in the opposite, the net impact on the Beveridge curve will be ambiguous.

AI may influence labor market matching through several channels (see Figure 2 below), with ambiguous impacts. Screening tools could for instance be utilized to improve labor market matching, reducing unemployment and vacancies (Broecke, 2023). At the same time, the disruptive nature of AI's development causes a skills mismatch (Gidehag, 2024). If the AI adoption outpaces the reskilling of the labor force, structural unemployment will likely increase. Furthermore, there is a trend toward labor market polarization from AI adoption. As middle-income professions – often considered relatively stable – are increasingly subjected to automation, they slowly disappear (Acemoglu & Loebbing, 2024). How the labor markets will respond to the change is ambiguous; will there be enough low- or high-income jobs created to offset the automation, keeping matching the same? Regional differences regarding labor market policies will also cause different outcomes on the labor market matching (Stephany & Teutloff, 2023). Furthermore, the impact on each industry will also differ since AI complementarity differs between them (Guarascio et al., 2025). As such, the impact within Europe is ambiguous; it is uncertain whether the average effect of labor market matching is positive or negative. It is likely that job vacancies and unemployment move in opposite directions.

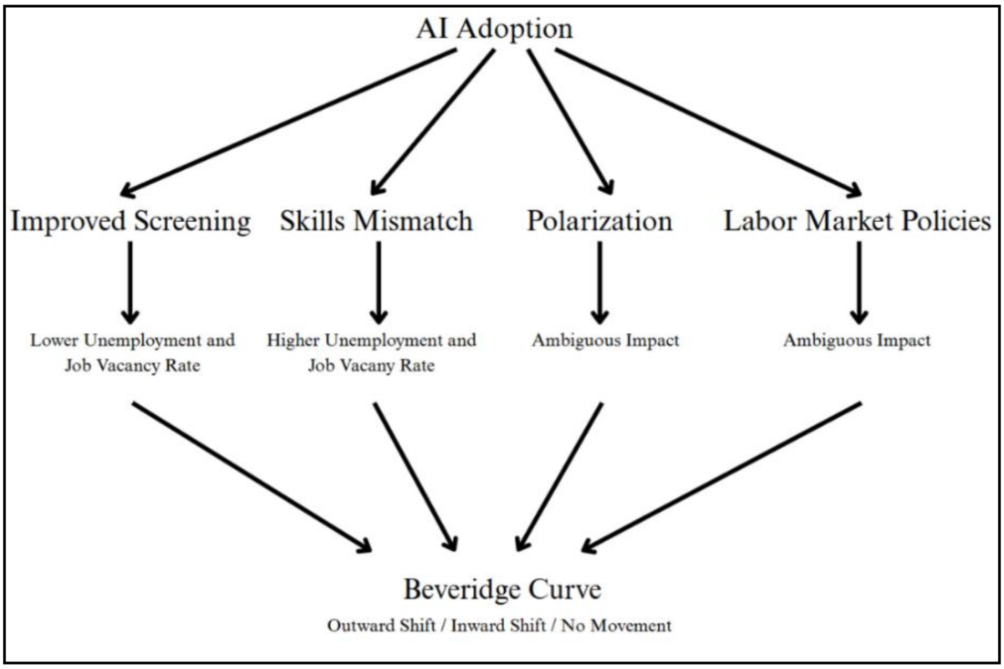

Figure 2. AI adoption's impact on the Beveridge Curve

3.4. Controls

It is important to control for population growth when estimating AI's impact on the labor market. If there is a growing working-age population with inadequate supply of job vacancies, the working age population increase will constitute an increase in unemployment and greater difficulties for new labor market entrants (ILO, n.d.)

Other factors impacting the Beveridge curve would be Business Cycles – which changes in both unemployment and growth in the short run. In the short run, the IS-LM model is used to describe shocks to money market- and goods equilibria at a given interest rate and output (Gottfries, 2013). As such, using these two dimensions as controls can reflect business cycles in the regression. In addition, there is also a strong relationship between unemployment and inflation described in the Philips curve; as inflation increases, unemployment will decrease in the short run (Gottfries, 2013). As such, it is a necessary variable to include in the regression.

Deeper theoretical insights of the controls can be read in Appendix II.

4. Data

For the regression analysis, panel data for regions and countries across Europe over the years 2020–2024 has been collected. Most of the data has been retrieved from Eurostat's database, with some complementary data sourced from OECD. The availability of data for our key variable, artificial intelligence, is limited, which constrains the panel to the years and geographical areas where AI data is available. Eurostat provides country-level data on AI for 2021, 2023, and 2024, and regional data for 2023 and 2024. This is a brief time span for a panel data regression, which must be kept in mind.[1]

The regions used as entities in the dataset are NUTS 2 regions, which is a classification developed by the EU to reference countries' regions for statistical purposes. While there are a total of 244 regions at the NUTS 2 level, AI data is not available for all of them. (Eurostat, n.d.) Therefore, our data set only includes 93 regions across twelve different countries. National-level data for 32 countries is also included to increase the number of observations. It should be noted that these are simply the countries and regions that the panel is based on, data is not available for all these entities for every variable in the data set. However, missing data is fortunately distributed evenly across regions and countries, suggesting that there are no systematically missing data points. A full list of all countries and regions included in the final regressions is shown in Table 6 in Appendix I.

4.1. Variables

To analyze whether AI has an impact on matching efficiency in the labor market we examine the independent variable AI (referred to as AI adoption and AI usage). The AI variable represents the percentage of enterprises who use AI in each region or country. It includes enterprises with at least ten employees in all sectors except the financial sector, agriculture, forestry and fishing, and mining and quarry. To incorporate the AI data from 2021, the missing NUTS 2 values were imputed with the corresponding national average. AI adoption rates vary across different high- and low-income regions and countries in Europe, with no

[1] Due to the limited number of years in the data set, observations that have been marked as "Observation flags" by Eurostat have been included in the dataset. This includes provisional data where final data were not yet published, observations with breaks in time series, observations where the definition differ, and some observations with low reliability.

systematic differences between them. As such, the dataset is sound for regression analysis, as there seems to be somewhat of a randomness involved in AI usage across Europe.

The main method used to investigate the relationship between AI and matching efficiency in this report is to include both dimensions of the Beveridge curve – the job vacancy rate and the unemployment rate – as dependent variables in separate regression models. Data for both variables have been sourced from Eurostat and ranges from 2020–2024. The unemployment rate variable reflects the percentage of unemployed people within the labor force. To classify as unemployed, an individual must be between the ages of 15 and 74, not be employed, currently available for work, and actively seeking work (Eurostat, n.d.).

The job vacancy rate variable represents the percentage of total job posts that are vacant and is calculated with the following formula:

$$Job\ Vacancy\ Rate = \frac{Number\ of\ Job\ Vacancies}{Number\ of\ Job\ Vacancies + Number\ of\ Occupied\ Posts} * 100.$$

It includes all sectors except the agriculture, forestry and fishing category, activities of households as employers, and activities of extraterritorial organizations and bodies. Since only quarterly data was available for the job vacancy rate, the average of the four quarters was calculated for each year to fit the panel with yearly data.

To test heterogeneity, regressions in different sectors are performed to analyze the relationship between AI and job vacancies across different industries. 'Administrative and support services', 'Manufacturing' and 'Information and Communication' are chosen as heavily AI exposed industries. 'Construction' is chosen as an industry that is less exposed to AI. The choices of industries were made in reference to the AIIE discussed in the theoretical framework (3.1.1).

To analyze the relationship between artificial intelligence and matching efficiency more extensively, our third model uses labor market slack as the dependent variable. The labor market slack measure refers to all unmet need for employment by including unemployed individuals, underemployed part-time workers, people who seek a job but are not available to work immediately, and people who are available to work but not seeking a job. By including the latter categories, the measure includes individuals who are not captured through the unemployment rate – these are called supplementary indicators to unemployment. The combination of the labor force and the potential additional labor force is referred to as the *extended labor force* and provides a more complete picture of the labor market (Eurostat 2024).

A list of all variables, their definitions, and their sources is displayed in Table 7 in Appendix I. The control variables and the reasoning for their inclusion in the regressions are further explained in section 5.1.

4.1.1. Handling Data Limitations

A problem encountered with the job vacancy variable was the limited availability of regional observations of job vacancy rates on the NUTS 2 level. To mitigate this problem, job vacancy data was searched for on databases of statistical authorities for countries where Eurostat did not provide regional job vacancy data. We found that the statistical authority of Denmark provided the job vacancy rate on a regional level and the statistical authorities of Spain and Austria provided data on the total number of job vacancies on the NUTS 2 level. By using this data, we were able to add 32 additional observations for each year to our dataset.[2] The total number of job vacancies was combined with Eurostat's employment data to calculate the job vacancy rate for the regions in Spain and Austria. A thorough description of these calculations can be found in Appendix I.

As for the AI variable, observations for some of the control variables have been imputed. Data on inflation, long-term interest rates, and short-term interest rates are collected on a national level. Therefore, the missing regional values were imputed with the corresponding national values, based on the assumption that these indicators do not vary across regions within the same country.

Another way of coping with the issue of missing data was to perform our own calculations. One challenge we encountered was that Eurostat does not provide data on real GDP in a consistent format across the national level and the NUTS 2 level. Therefore, a measure for real GDP was constructed to ensure comparability between regions and countries, using data on nominal GDP and inflation from Eurostat. Furthermore, real GDP growth and population change have been calculated using the constructed real GDP measure and the population data from Eurostat. Descriptions for these calculations are found in Appendix I.

[2] NUTS 2 data on job vacancies was not available for different sectors in these countries. Therefore, we were not able to increase the number of observations for the separate industries.

The issue with the approach of using real GDP and interest rate to account for cyclical fluctuations is the skewness of the real GDP distribution. However, to capture cyclical changes, the given output level is not of interest; real GDP growth is as informative for capturing cyclical fluctuations.

As explained, because values are missing from some regional observations, values at the country level have been imputed instead. For example, the country's AI usage rate has been imputed for the regions missing values for certain years, such as the regions in Denmark in 2023. This is done to increase the number of observations in the dataset. A concern of imputed values is that underlying heterogeneity is omitted, potentially biasing the dataset. For instance, it may be that AI is more used in the capital of Denmark than the rest of the country – which is the case in Belgium. If so, imputed values will distort the underlying data, yielding unreliable regressions. The issue with the conditional-mean or proportions imputation is that they exaggerate the relationships between variables. Simultaneously, imputed values are treated as certain and stand on equal footing with non-imputed ones (Austin et al., 2021). As such, results from regression analyses must be interpreted with some caution.

The dataset contains enough observations for the central limit theorem (CLT) to hold. According to the CLT, for an average to approximate an underlying normal distribution, a minimum of 30 observations are required as a rule of thumb. Accordingly, Ordinary Least Squares (OLS) assumption 1 – that the error terms will be normally distributed – can be considered to hold, and statistical inference can be performed. (Jaggia & Kelly, 2022; Stock & Watson, 2020). Thus, to infer any population characteristics below the threshold is considered invalid. However, due to high skewness, regression at the 30-observation threshold may provide unstable estimates due to a higher variance. Fortunately, the datasets used in the regression analysis reach far above the threshold; concerns regarding the normality assumption should be mitigated. As Kwak and Kim also (2017) note, increasing the sample size will cause a decrease in the variance. Underlying assumptions of CLT are tested through plotting residuals on a probability plot to determine dataset robustness in the results.

To reduce the skewness of the underlying distributions, some variables have been transformed using logarithms. As such, the influence of outliers on overall results is mitigated, while the transformed variables simultaneously better approximate the bell-shaped curve. Furthermore, it will allow regression models to capture non-linear relationships. The transformation has been made for AI usage rate, unemployment rate, job vacancy rate, and labor market slack. All these variables show positive skewness, which is displayed in Figures 14-17 in Appendix

I. Furthermore, residual plots have been examined to ascertain that these transformations improve model fit and are appropriate.

Intuitively, log-transforming the AI variable and the dependent variables for matching efficiency is appropriate. If there is an effect, it is reasonable to expect diminishing marginal effects of AI usage; for instance, an increase from 5% to 10% in AI usage may have a greater impact on matching efficiency than an increase from 90% to 95%. Log-transforming the AI variable helps capture this potential non-linearity.

This intuition can be illustrated by comparing three countries in our dataset – Greece, Spain, and Luxembourg – between 2021 and 2023. These countries experienced a similar increase in AI usage in percentage points (1.37, 1.51, and 1.45) but differed in total AI usage levels. As shown in Figure 3, the countries with lower initial AI usage, and therefore higher relative increase, exhibit greater changes in matching efficiency. While this observation is not causal, it visually supports the expectation of diminishing marginal effects. Additionally, Graetz and Michael (2018) finds evidence of diminishing marginal productivity gains from increased use of robots. While their study focuses on robots and productivity rather than artificial intelligence and matching efficiency, the underlying logic of diminishing returns to technology adoption supports the expectation that AI usage may similarly exhibit non-linear effects, if such effects exist.

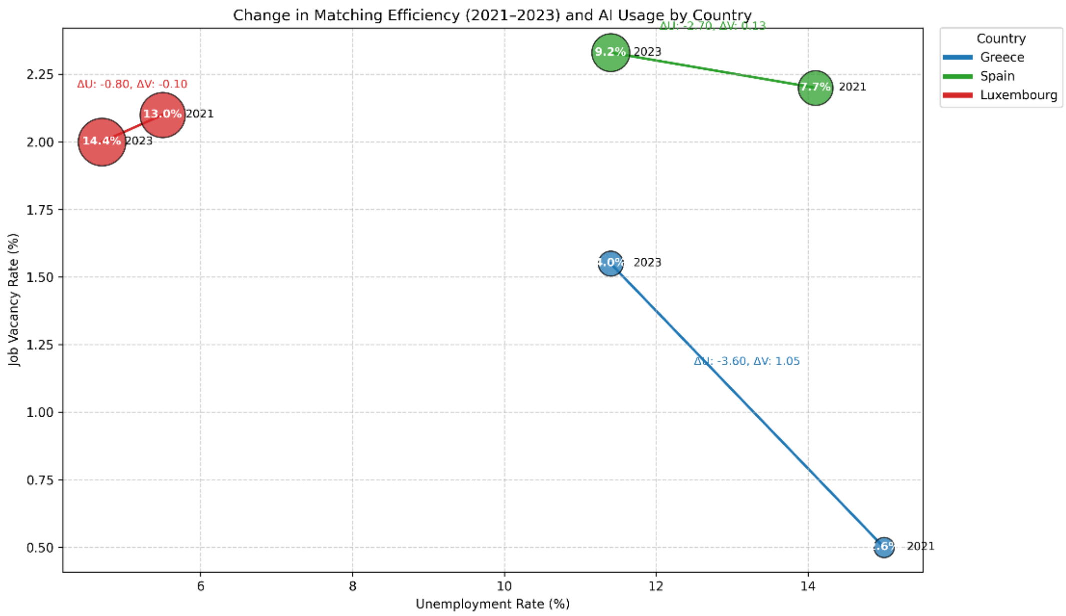

Figure 3. The graph displays a version of the Beveridge curve which includes the countries Greece, Spain, and Luxembourg from our dataset. The graph only includes the years 2021 and 2023. Additionally, the size of each Beveridge point corresponds to the usage of AI in the country and year observed – larger bubble = higher share of enterprises who uses AI. This illustrates the change in matching efficiency from 2021 to 2023 while also showing the difference in total AI adoption between each observation.

Furthermore, since these variables are measured in percentages, it is meaningful to estimate the relationship in terms of elasticities – the percentage change in one variable resulting from a percentage change in another variable. Stock and Watson (2020) state that a log-log model is appropriate when you are interested in estimating elasticities, which further supports our use of log-transformations for both independent and dependent variables.

4.2. Descriptive Statistics

Table 2 displays descriptive statistics for all core variables in the dataset. The table reveals that the job vacancy rate limits the analysis with its small number of observations even after adding our own calculated values. The lack of observations for job vacancies depends on the fact that there are regions and countries in the dataset where it is not measured. For the GDP variable, data was unavailable for the year 2024. This problem, however, was handled by lagging the real GDP growth variable.

Table 2. Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Geo ID (Spatial units)	375				
AI	375	8.79	6.17	0.15	34.97
	(375)	(1.91)	(0.80)	(-1.90)	(3.55)
Unemployment rate	314	7.13	4.68	2.1	30.8
	(314)	(1.80)	(0.54)	(0.74)	(3.43)
Job vacancy rate	270	1.76	1.51	0.07	11.10
	(270)	(0.25)	(0.84)	(-2.59)	(2.41)
Labor market slack	372	12.43	6.61	2.5	40.2
	(372)	(2.39)	(0.52)	(0.92)	(3.69)
Real GDP growth	306	-0.97	6.38	-27.49	26.88
Population growth	303	3.22	0.94	-4.31	4.91
Education	371	80.17	11.49	41.2	97.8
Tertiary education	314	35.25	11.16	12.3	62
Long-term interest rate	362	2.72	2.26	-0.51	7.57
Short-term interest rate	345	2.50	3.38	-0.43	13.64
Inflation	375	4.96	5.01	0.6	58.5
High-tech sector	362	4.67	2.41	0.8	14.1

The table presents descriptive statistics for all variables used in the regressions for the years 2021, 2023, and 2024. The values for real GDP growth, long-term interest rate and short-term interest rates are for the years 2020, 2022, and 2023 since these variables are lagged in the regressions. Log transformations are shown in parentheses.

There is considerable variation in the AI adoption rate in the dataset, with AI usage ranging from 0.15% to 34.97% with a standard deviation of 6.17%. This also applies to the unemployment rate, which ranges from 2.1% to 30.8% and has a standard deviation of 4.68%. In contrast, the variation is less pronounced for the job vacancy rate which ranges from just 0.07% to 11.1% with a standard deviation of 1.51%. This suggests that the job vacancy rate is similar and low across most areas, with a few outliers showing unusually large vacancy rates, whereas the unemployment rates vary more substantially across spatial units.

Labor market slack has a greater minimum and maximum value (2.5% and 40.2%) than the unemployment rate, as well as a higher standard deviation (6.61%). These differences indicate that running separate regressions on each of these variables is appropriate and provides additional insights into labor market matching efficiency. In addition, all independent and dependent variables (AI, job vacancies, unemployment, and labor market slack) have a minimum value larger than zero – ensuring that they can be log-transformed as they are.

Table 8 in Appendix I presents descriptive statistics for AI adoption and job vacancies for each of the industries used to test heterogeneity. It shows that these regressions are even more limited by the amount of job vacancy observations, which is primarily due to the statistical bureaus of Austria, Spain, and Denmark not providing industry specific data on a regional level. Furthermore, clear differences can be observed for both variables across the industries. The administrative and support service sector has the highest variation in job vacancies (Min = 0.1%, Max = 15.75%, SD = 3.12%, Mean = 2.95%) and the manufacturing sector has the lowest variation and overall lowest values (Min = 0.30%, Max = 4.33%, SD = 0.99%, Mean = 1.62%). However, the dispersion across industries is even greater for AI usage. The communication and information sector has the highest adoption rate (Min = 1.56%, Max = 90.48%, SD = 18.33%, Mean = 35.43%) and clearly differs from the construction sector (Min = 0.13%, Max = 19.08%, SD = 3.72%, Mean = 4.65%), which has the lowest AI usage rate.

Figure 13 in Appendix I presents a heat map correlation matrix of all base variables in the dataset. To address multicollinearity, which arises when regressors are highly correlated (Stock and Watson 2020), we use the change in population and real GDP as control variables instead of the total values, since they are highly correlated. The matrix also reveals a strong positive relationship between unemployment and labor market slack. This is expected, as labor market slack is an extension of the unemployment rate. However, this correlation is not an issue since labor market slack and unemployment are used as separate dependent variables.

4.3. Visual Insights

To get a first impression of the relationship between artificial intelligence and matching efficiency in the labor market, we list statistics and plots of the use of AI. Figure 4 shows a map of the countries included in the dataset and the share of enterprises using AI in each country. The image shows that the northern countries have a darker shade of blue, meaning that AI usage is high among enterprises in these countries, while most eastern European countries have a lighter shade of blue, indicating that AI usage is not as common among enterprises in these countries. Denmark is at the top of the list in 2024, with 27.58% of enterprises using AI, while Romania is at the bottom of the list, having 3.07% of enterprises using AI in the same year. The figure is complemented with Figure 18 in Appendix I, which displays AI usage across countries over the years 2021, 2023, and 2024. The chart displays significant differences between countries as well as the rapid increase in AI usage in recent years in some countries.

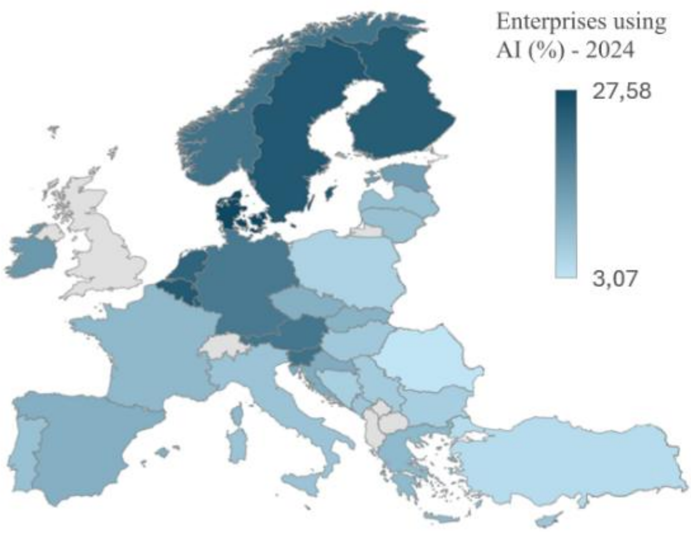

Figure 4. AI usage among countries in the dataset. Countries with the color gray are not included in the dataset.

Figure 5 displays a Beveridge curve for the countries in the panel. Instead of looking at changes in the curve over time, this graph shows the average Beveridge point in 2024 for each country. The sizes of the Beveridge points are determined by the share of enterprises using AI in the country. A larger bubble size means that a larger share of enterprises uses AI in that country, and vice versa for smaller bubbles.

By observing the Beveridge curve, it is visible that the three countries with the highest job vacancy rate, Belgium, Austria, and the Netherlands, all have a relatively high AI adoption rate, while the three countries with the lowest job vacancy rate, Poland, Bulgaria, and Romania, all have a relatively small AI adoption rate. Looking at the unemployment rate, the relationship is not as clear. Spain and Greece, who have the highest unemployment rates, have a similar AI adoption rate to Czech Republic, who has the lowest unemployment rate.

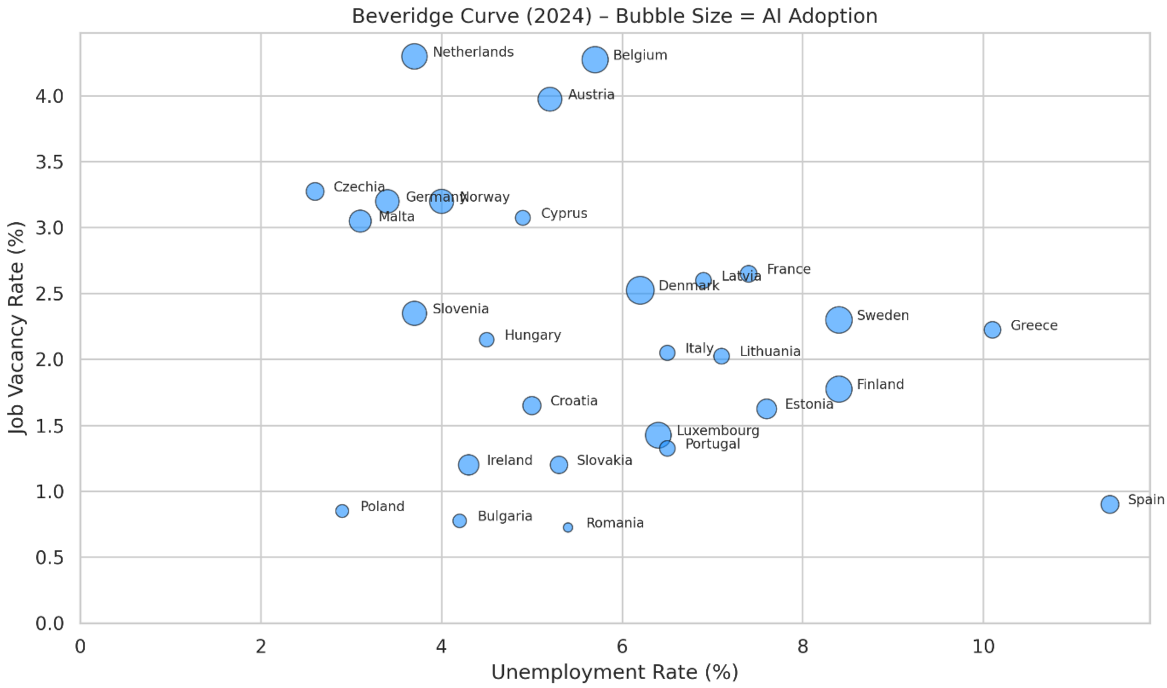

Figure 5. The Beveridge curve combined with AI usage in 2024 for countries in the dataset – a visual representation that highlights the relationship between artificial intelligence and both unemployment and job vacancies. The size of the bubbles corresponds to the share of enterprises that use AI. A smaller bubble represents a lower AI adoption rate while a larger bubble represents a higher AI adoption rate.

When comparing Beveridge points, a low unemployment rate and high job vacancy rate are considered to represent a tight labor market, while a high unemployment rate and low job vacancy rate are considered to represent a slack labor market (Eurostat, 2024). By using this logic and observing the Beveridge curve for 2024, it would be reasonable to assume that Spain had a relatively slack labor market while Czech Republic and the Netherlands had a relatively tight labor market.

However, it is difficult to see a clear relationship between matching efficiency and AI usage by simply observing this bubble plot with the eye. To complement it, we look at unemployment and job vacancies separately in Figure 6 and 7. Figure 6 plots the relationship between unemployment and AI usage in enterprises across European countries, with unemployment on the y-axis and AI adoption rate on the x-axis. The scatterplot displays no clear relationship between the two variables. Figure 7 plots the relationship between job vacancies and AI adoption, displaying a moderate positive relationship between AI and job vacancies.

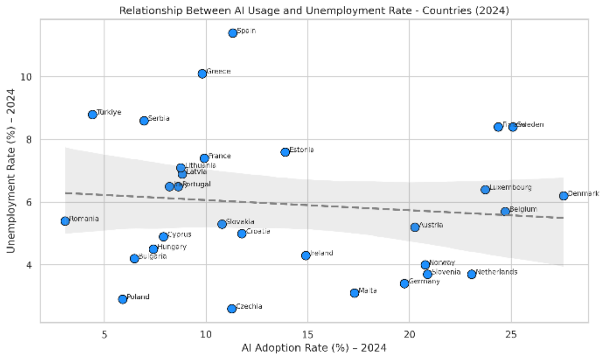

Figure 6. Unemployment and AI usage in 2024. (30 observations) Correlation = -0.11, p-value = 0.58.

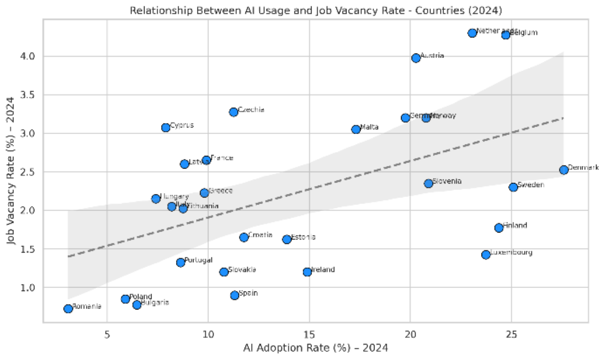

Figure 7. Job vacancy rate and AI usage in 2024. (28 observations) Correlation = 0.51, p-value = 0.006.

However, these plots only show observations on a national level in the year 2024 and thus, many observations in the dataset are excluded. Figure 19 and 20 in Appendix I display two similar plots but include all observations, for both regions and countries, in the years 2021, 2023, and 2024. As in Figure 7, Figure 19 illustrates a positive and statistically significant relationship between artificial intelligence and job vacancy rate – although a smaller correlation (0.37). Unlike in Figure 6, there is a significant negative relationship between AI and unemployment when including all observation, but the correlation is still weak (-0.13).

In addition, Figure 21 in Appendix I presents a corresponding scatterplot between AI adoption and labor market slack, where no clear correlation can be seen. Still, there are observable differences between this relationship and the relationship between AI and unemployment, further strengthening the argument for using both factors as separate indicators for matching efficiency.

On the next page, figures 8 to 11 display the relationship between artificial intelligence and job vacancy rate in the four different sectors used for Equation 4. There are some differences between the sectors, but they are similar overall, showing a positive and statistically significant relationship between usage of artificial intelligence and job vacancies. The two industries that stand out are the information and communication sector and the administrative and support services sector. The information and communication sector has the highest correlation coefficient among the four industries, while the administrative and support services have the lowest correlation coefficient. Both these industries are considered as sectors with relatively high exposure to AI.

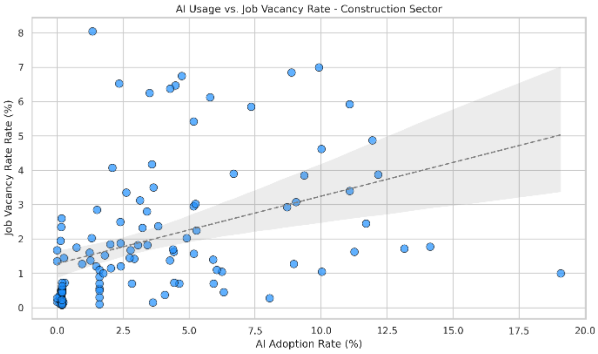

Figure 8. AI and vacancies in the Construction sector.
Correlation = 0.40, p-value = 0.000

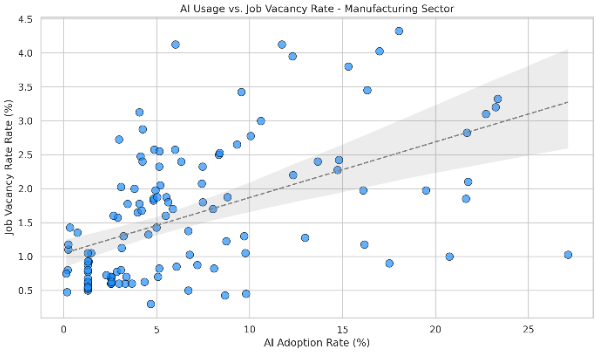

Figure 9. AI and vacancies in the Manufacturing sector.
Correlation = 0.51, p-value = 0.000

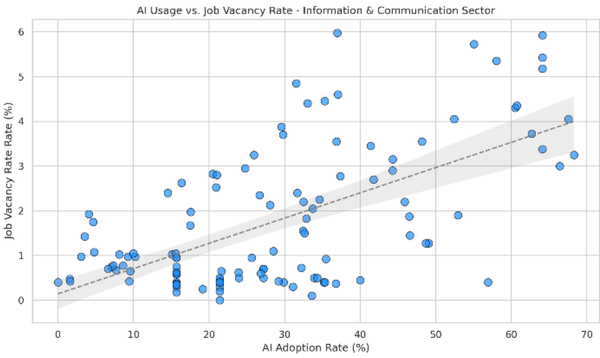

Figure 10. AI and vacancies in Information and communication.
Correlation = 0.62, p-value = 0.000

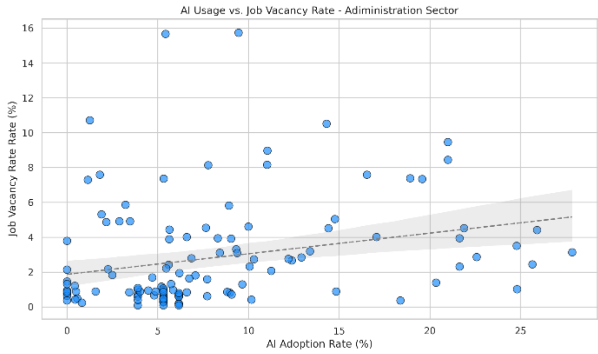

Figure 11. AI and vacancies in Administrative and support services.
Correlation = 0.26, p-value = 0.004

5. Model Specification

The models constructed to measure AI's impact on the Beveridge curve are the following:

$$lnUnemployment_{it} = \beta lnAI_{it} + \gamma Controls_{it} + \delta_t + \alpha_i + \varepsilon_{it} \quad (1)$$

$$lnJob\ Vacancies_{it} = \beta lnAI_{it} + \gamma Controls_{it} + \delta_t + \alpha_i + \varepsilon_{it} \quad (2)$$

$$lnLabor\ Market\ Slack_{it} = \beta lnAI_{it} + \gamma Controls_{it} + \delta_t + \alpha_i + \varepsilon_{it} \quad (3)$$

$$lnJob\ Vacancies_{it}^{(Ind)} = \beta lnAI_{it}^{(Ind)} + \gamma Controls_{it}^{(Ind)} + \delta_t^{(Ind)} + \alpha_i^{(Ind)} + \varepsilon_{it}^{(Ind)} \quad (4)$$

The model is an OLS panel data regression with both time fixed (δ) and unit fixed (α) effects transformations. Time fixed effects are specified to be annually – whereas unit fixed effects are set for each region or country within the European Union. By including time and unit fixed effects, unobserved characteristics that are invariant across time and space are included in the regression, mitigating eventual biases from panel data estimation (Stock & Watson, 2020). These two transformations will enable different intercepts for each region and year in the OLS estimation strategy. Additionally, standard errors are clustered at the regional- or country level to account for serial correlation and heteroskedasticity (Stock & Watson, 2020). To investigate multicollinearity in the model, each regression will be conducted once more without using unit fixed effects. Afterwards, a VIF test will be performed on the variables to improve model robustness. This is done as a VIF test cannot be performed on a unit fixed effect regression.

A fixed effect regression was preferred over a random effect model due to the assumptions made. A random effect model assumes that that predictor and individual specific effects are uncorrelated (Hausman, 1978). However, this assumption is violated in our context since the adoption and usage of AI is likely endogenous to broader labor market conditions. For instance, sectors may adopt AI due to labor shortages; if so, the random effects model specification will not work. Therefore, the fixed-effects regression which allows for correlations between individual effects and regressors is more suitable.

To estimate the impact of artificial intelligence on the Beveridge curve, a plethora of regressions are performed to effectively map out the relationship between artificial intelligence and labor market matching efficiencies. To prove that AI constitutes a significant impact on the Beveridge curve, both unemployment and job vacancies are regressed on AI. If the regressions provide significant results, it will imply that the Beveridge curve has shifted due to AI usage. In what direction depends on the sign of both job vacancy- and unemployment rates. If the results are insignificant, it cannot be assumed that the Beveridge curve has shifted. To investigate model robustness, unemployment is swapped with labor market slack in one of the specifications. In addition, the regressions will be run at the regional level solely to further elevate model soundness.

As discussed in the theory, AI exposure is heterogenous across industries. Consequentially, the overall impact on the regional and country labor markets will differ based on the AI exposure in each region, country and industry. Therefore, regressions of AI usage on certain industries' job vacancies are run to uncover expected heterogenous impacts on labor markets. Neither labor market slack nor unemployment can be used as an outcome variable since they are never limited to a single industry; individual unemployment cannot possibly be restricted to one type of profession or industry. Therefore, only job vacancies at the industry level will be investigated. This is regardless sufficient to identify sectoral heterogeneity in AI's impact, since differing job vacancies across industries indicate the ambiguous impact of AI usage.

Only certain industries will be chosen, as investigating individual industry's impact is beyond the scope of the thesis

5.1. Controls and Limitations

As described in the theoretical framework, there is a strong relationship between inflation and job vacancies. The Beveridge curve measures the relationship between unemployment and job vacancies, keeping everything else constant. As such, both dependent variables are needed as controls for each other's regressions, as the result otherwise will be biased. Otherwise, there will be omitted variable bias (OV-bias) concerns (Stock & Watson, 2020), and the validity of the estimates will come into question. To avoid issues of endogeneity within the models, both variables are lagged by a year to predict the outcome variables. Although there is no adequate robustness proxy for job vacancies, there are unemployment proxies. For instance, as described in the data section, labor market slack is a more extensive metric for unemployment. As such, it can constitute a sound substitute, both as a dependent or independent variable. Furthermore, as the labor market slack is a more extensive measurement, it may highlight broader changes in matching efficiency.

5.1.1. Cyclical Controls

Chosen variables to control for short-run fluctuations in unemployment were short-term interest rate, real GDP and inflation. Using both real GDP and short-term interest rate variables as controls will find where the region or country is on the IS-LM curve (see Appendix II). Thus, the two variables will provide annual snapshots of the positions each region or country is at on the IS- and LM curves. For robustness tests, short term interest rates will be swapped with long term interest rates for the regions and countries.

According to Gottfries (2013), lagging real GDP growth and short-term interest is reasonable as cyclical effects have a lagged impact to begin with (See Appendix II). This is also beneficial as real GDP as well as interest rates may be impacted by current labor market conditions and hence endogenous. Furthermore, lagging the short-term interest rate mitigates correlation with inflation and in turn multicollinearity concerns.

Building on the Philips curve presented in Appendix II, there is a relationship between inflation rate and unemployment. As inflation increases, unemployment should decrease.

Therefore, it is another important control for short-term fluctuations in unemployment. Similar concerns must be raised regarding population growth (see Appendix II). Sudden shifts in demography could impact labor markets. Including both inflation and population growth is therefore a must.

5.1.2. Structural Controls

The model must also account for structural differences across regions. As previously established, educational and development levels within a region significantly affect innovation adoption. Excluding controls for education will lead to OV-bias in the results, which occur when an unobserved variable is correlated with the included regressor as well as the dependent variable. Due to correlation concerns at the regional level, a wider education level is selected instead of tertiary education. Tertiary education will instead be used in robustness tests. Chosen variable to proxy level of education is the share of population aged 25 - 64 with upper secondary, post-secondary, non-tertiary or tertiary education, measured in percent. Choice of educational variable can be read further in Appendix II.

As AI is on the technological frontier, it is also necessary to include employment in high-tech sectors as a control variable for the different regressions. More individuals employed in cutting edge industries should correlate strongly with AI usage. Therefore, it may be a confounder, since there could be higher natural matching inefficiencies/efficiencies on the high-tech labor market. GDP per capita, which is an important structural determinant of AI adoption is indirectly included in the regression through fixed effects and changes in population growth and real GDP growth. As such, all important structural controls are used in regression.

5.1.3. Additional Omitted Variables

As explained in section 3.2.2., wages are a key factor influencing unemployment. However, no suitable data or proxy for wages has been found, leading to the exclusion of any wage control variables in the models. The omission of a wage variable is a clear shortcoming in the model that must be kept in mind when interpreting the results as it will likely lead to OV-bias.

Moreover, Empirical evidence shows that the elderly are generally less prone to embrace new technology (Bertolazzi et al., 2024). Simultaneously, there is evidence of the age of the population directly impacting employment rates in the economy (Carlsson & Eriksson, 2019). Therefore, population age will be predictive on both the Beveridge curve and the AI usage in the region. However, due to overlap in its influence on both the predictor and outcome variables age has been excluded from the regression. This is a well-documented issue for certain socioeconomic variables. For instance, in the report by Senik (2008), age is excluded in the life income on well-being regression since it likely will impact both the predictor and outcome variable.

5.1.4. Lagged Effects and Causality

One concern with the model is the exclusion of lagged effects for some of the variables due to limited data availability, such as AI usage rate for instance. As the data is limited to a short period of time, lagged effect regressions will not be robust. Even if it would be econometrically sound to lag the effects in reference to Appendix II – it is simply not possible with the data at hand. Therefore, estimates may reflect short-run correlations rather than true lagged effects. It may be that estimated impacts stem from the year or years prior.

It is also important to highlight the issue of reverse causality; it cannot be determined in which direction the causality between AI and labor market slack runs. It is also a possibility that increased AI adoption may be in response to rising vacancies or unemployment. To prove robustness in the direction of causality, a Granger causality test can be conducted (Wei, 2016). However, the lack of available data is insufficient to estimate lagged effects; a minimum of eight time periods are required for the Granger causality test. As data from Eurostat accumulates in the future, the test can be performed. Therefore, the regression will provide correlational information rather than causal inference. Building on previous literature for now, there is a documented unidirectional relationship between AI and low-skill employment (Giwa, 2024). This is at least indicative of a causal relationship for matching efficiency. However, to estimate a true causal effect, an IV-instrument for AI would be required, which has unfortunately not been found.

6. Results

The regression results assessing the impact of artificial intelligence matching efficiency are displayed in Table 3. A significance level of 5% is used throughout the report.

Table 3. Regression results for Models 1-3.

VARIABLES	(1.1) UNEMPLOYMENT RATE (All)	(1.2) UNEMPLOYMENT RATE (Regions)	(2.1) VACANCY RATE (All)	(2.2) VACANCY RATE (Regions)	(3.1) LABOR MARKET SLACK (All)	(3.2) LABOR MARKET SLACK (Regions)
Ln AI	**-0.030**	**-0.036**	**-0.021**	**-0.080***	**-0.047***	**-0.050****
	(0.028)	(0.030)	(0.053)	(0.044)	(0.025)	(0.023)
Lagged ln unemployment			-0.160	-0.057		
			(0.145)	(0.123)		
Lagged ln vacancy rate	-0.135***	-0.095			-0.116*	-0.007
	(0.049)	(0.079)			(0.058)	(0.067)
Population change	-0.031**	-0.058*	0.003	0.090	0.038	-0.068*
	(0.013)	(0.031)	(0.038)	(0.055)	(0.031)	(0.036)
Lagged short-term interest	0.029***	0.031***	-0.016*	-0.009	0.013***	0.008
	(0.005)	(0.007)	(0.008)	(0.010)	(0.004)	(0.005)
Lagged real GDP growth	-0.007***	-0.009***	0.011**	0.015***	-0.005***	-0.005**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)
Inflation	-0.009***	-0.012***	0.008	0.010*	-0.007***	-0.008***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)
Education	-0.028***	-0.033***	0.027	0.021	-0.029***	-0.036***
	(0.008)	(0.010)	(0.018)	(0.019)	(0.008)	(0.010)
High-tech sector	0.020	0.004	-0.007	0.007	0.001	-0.005
	(0.032)	(0.036)	(0.045)	(0.046)	(0.029)	(0.027)
2023	-0.022	0.001	-0.043	-0.168**	-0.077**	-0.037
	(0.035)	(0.044)	(0.055)	(0.078)	(0.029)	(0.039)
2024	-0.109**	-0.082	-0.016	-0.096	-0.090*	-0.045
	(0.045)	(0.063)	(0.058)	(0.078)	(0.049)	(0.061)
Constant	4.035***	4.463***	-1.542	-1.352	4.815***	5.384***
	(0.666)	(0.786)	(1.295)	(1.384)	(0.684)	(0.796)
Observations	221	143	221	143	221	143
R-squared	0.477	0.526	0.187	0.238	0.501	0.560
Number of spatial units	74	48	74	48	74	48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the main regressions for interpreting the impact of AI on labor market matching in the years 2021, 2023, and 2024. It includes two regressions each for the dependent variables unemployment rate (Model 1), job vacancy rate (Model 2), and labor market slack (Model 3) – one that includes all observations (countries and NUTS 2 regions) and one that only includes regions as spatial units.

The impact of AI adoption on the unemployment rate are statistically insignificant at the 5% level, both for all observations and when only including regions (Models 1.1 and 1.2).

Therefore, it cannot be concluded that the use of AI has a significant effect on unemployment. The results are consistent across the two models, both of which show a relatively high R-squared (0.477 and 0.526), indicating that a considerable amount of the variation in unemployment is explained by the included variables. This consistency suggests that the insignificant results are relatively robust. However, there may be omitted variable bias in the model, for example due to exclusion of a wage-related variable which is a key factor in explaining unemployment.

Similarly, the impact of artificial intelligence on the job vacancy rate is statistically insignificant at the 5% level in both Model 2.1 and 2.2 – and therefore there will be no further comments on these coefficients. As for the unemployment rate, it cannot be concluded that AI usage has a significant impact on job vacancies from these results. These results differ from the correlation coefficients in section 4.3 which suggested a positive relationship between AI and job vacancies, indicating that the regression models account for confounding factors by including fixed effects and additional controls. However, the results show a relatively small R-squared for both models (0.187 and 0.238), indicating omission of some important variables. Thus, the regression results of the job vacancy rate must be interpreted with caution since it is unclear whether the inclusion of these omitted variables would strengthen or weaken the relationship between AI and job vacancies.

In the context of the Beveridge curve, these findings suggest that a decrease or increase in AI adoption does not appear to shift the curve in a significant way. Both dimensions of the curve, unemployment and job vacancies, are seemingly unaffected by the change in AI usage. This implies that when using the Beveridge curve as a measure of matching efficiency in the labor market, we cannot conclude that AI has a statistically significant impact on labor market matching based on our results.

When substituting unemployment for labor market slack, the effect of AI usage is statistically insignificant in the model with all observations (Model 3.1) at the 5% significance level, but significant in the model that only includes regions as spatial units (Model 3.2). The “regional models” were included to control for the fact that regions and countries are different observational units and may therefore not be appropriate to compare. As the results show, all regional models have a higher R-squared than the models that include all observations (although, consequently with less observation). This suggests that there may be flaws in comparing regions to countries and thus, the regional models are considered as the most robust and correct models. The result that indicates that AI has a significant negative impact on labor market slack is therefore considered the most robust and correct result.

In Model 3.2, a 1% increase in AI usage corresponds to a 0.05% decrease in labor market slack on average, net of other effects. As it is a log-log specification, the impact on labor market slack by adopting AI will be more economically significant at lower levels of AI usage. For instance, Melilla in Spain is the region with the lowest usage of AI in the dataset – a mere 1.46% of enterprises using AI in 2024. If they were to double the AI usage rate from 1.46% to 2.92% this would correspond to a 100% increase in usage. In turn, this would on average correspond to a decrease in labor market slack by approximately 3.53% – equivalent to a reduction from 34.7% to approximately 33.48% – a significant economic impact on the labor market, ceteris paribus. On the other hand, Midtjylland in Denmark – who was the region with the highest AI usage in 2024 – would have to increase AI usage by a total of 34.97 percentage points to double AI usage. The massive investments and infrastructure required would only yield an average 3.53% decrease in their labor market slack, all else equal. Naturally, if the labor market slack is particularly high, such as in Ceuta, Spain, who had an average labor market slack of 35.3% in 2024, the 3.53% average decrease may still be economically significant even at the higher levels of AI usage. Therefore, if a region has a combination of low AI usage and high labor market slack, like Melilla, the adoption of AI can have large matching efficiency implications.

The regressions for unemployment and labor market slack have a rather high R-squared, which suggests model overfitting. Overfitting will constitute an issue for generalizability. When modelling complex relationships, it should not be expected to achieve a high R-squared, as the relationships between underlying factors are too difficult to model (Frost, n.d.). Therefore, regression results must be interpreted with caution, as the model may capture much random noise. However, it should be noted that the regression performed similarly when some observations were excluded, which indicates model robustness.

6.1. Industry Heterogeneity Results

Regression results for industry heterogeneity can be read below. The results in regression 4.1, which exclude the high-tech control variable and the year 2021 are consistent with the results in regression 2.1. This ensures that the industry specific regressions are comparable to the model which includes all industries. There are clear differences between the regression results and the simple correlation coefficients displayed in section 4.3, suggesting that the regression model accounts for confounding factors.

Table 4. Regression results for Model 4.

VARIABLES	(4.1) VACANCY RATE (All)	(4.2) VACANCY RATE (Administration)	(4.3) VACANCY RATE (Information)	(4.4) VACANCY RATE (Manufacturing)	(4.5) VACANCY RATE (Construction)
ln AI	**-0.058**	**-0.012**	**-0.286****	**0.010**	**-0.077**
	(0.037)	(0.134)	(0.137)	(0.057)	(0.063)
Lagged ln unemployment	0.137	0.002	1.226*	0.019	-0.242
	(0.226)	(1.018)	(0.703)	(0.481)	(0.611)
Inflation	0.007	0.041*	0.016	0.007	0.015
	(0.005)	(0.023)	(0.018)	(0.007)	(0.011)
Education	-0.011	0.429***	-0.045	0.006	-0.023
	(0.023)	(0.123)	(0.078)	(0.042)	(0.078)
Population change	0.033	-0.125*	0.068	-0.013	-0.111
	(0.034)	(0.074)	(0.121)	(0.058)	(0.121)
Lagged short-term interest	-0.003	-0.111*	0.011	0.005	-0.030
	(0.020)	(0.065)	(0.056)	(0.030)	(0.047)
Lagged real GDP growth	0.001	0.002	0.008	-0.001	0.003
	(0.002)	(0.004)	(0.007)	(0.003)	(0.003)
2024	0.006	0.130	0.085	-0.131	0.201
	(0.057)	(0.233)	(0.174)	(0.091)	(0.179)
Constant	1.132	-35.093***	2.674	-0.302	2.566
	(1.895)	(11.407)	(6.757)	(3.502)	(6.002)
Observations	90	83	87	90	80
Number of spatial units	45	45	45	45	45
R-squared	0.357	0.508	0.317	0.322	0.191

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the regressions used to interpret if there is industry heterogeneity for the relationship between AI and job vacancies. It includes five regressions – each regression uses the same model (Model 4), but on five separate panel datasets. There is one dataset including all sectors and one dataset each for the sectors Administrative and support (Administration), Information and communication (Information), Manufacturing, and Construction. These models use the same controls as Model 2 apart from the omission of the high-tech industry variable, since it does not make sense to include when looking at different industries, and the omission of year 2021 since industry specific data is not available for this year.

Artificial intelligence is insignificant at the 5% level of significance for all industries besides the information industry. What this indicates is a heterogeneity in the impact of AI on the vacancy rates, and in turn the Beveridge curve. On average, the impact for the information and communication industry is a 0.286% decrease in vacancies as AI increases by 1%, ceteris paribus – an economically substantial impact within the industry. For instance, a 100% increase in AI usage would be equal to a decrease of approximately 21.93% in job vacancy rate, holding all other factors constant. At the same time, the other chosen industries have insignificant results, pointing to AI having no impact on the number of vacancies. As such, it can be stated that there likely is heterogeneity between industries.

To explain the change in the context of the conceptual framework, the Beveridge curve would shift downwards for the information and communication industry, while the curve would seemingly remain at the same vertical position for the other industries. The downward shift would be substantial at lower levels of AI usage and taper off as the adoption rate increases.

It is important to note that the time series depth is only two years for the industry comparison, meaning that there are fewer observations. Therefore, the reliability of the regression results can be questioned. Issues of reliability can also be shown through high standard errors within the regressions; both administration and manufacturing have a standard error that substantially exceed their respective conditional means of AI usage rate impact. While the omission of some potential confounders may have contributed to the variability, it is implausible that their exclusion alone could account for the observed differences. As such, it is unlikely that the observed differences are only due to omitted variables; evidence suggests there is likely a difference in the impact AI has on job vacancies.

In addition, the large constant in Model 4.2 suggests that there is a problem with the specification. The abnormal coefficient value is likely an effect of a bias in the model, mainly caused by the education variable. However, since this was only an issue in one of the models, education is included as a control variable in the model to compare regressions with the same controls.

6.2. Model Robustness and Causal Claims

The regressions have been re-estimated once more but without unit fixed effects to conduct VIF tests for each of the main models. A general rule of thumb is that a VIF score of 4 should be investigated further. If the VIF score approaches 10 or above, the multicollinearity is severe (Penn State, n.d.). The VIF tests suggest limited multicollinearity in the regressions. Across the regressions there is one control variable – education – that recorded VIF score above 4 (See Table 13, Appendix III). This is expected as we know that educational attainment and unemployment are negatively correlated. While the score of the education variable suggests moderate multicollinearity in the job vacancy regression analysis, it is not large enough to require corrective action. The average VIF score across all models is below 4, meaning that overall multicollinearity is low. As such, the original model specification was retained due to the variables' theoretical relevance and overall acceptable VIF-levels.

To assess the behavior of the error term, residuals are plotted for each regression model with all variables and observations included. No patterns can be found in their distribution for any of the regressions except for the administration industry mentioned above, which indicates randomness in the error term. Probability plots also show that the residuals are approximately normally distributed, following the diagonal line closely. Therefore, it can be concluded that although some omitted variables may exist, they do not cause systematic error terms.

To assess model robustness, several alternative regressions were estimated (see Appendix III) Replacing the short-term interest rate variable with the long-term interest rate variable causes changes in the significance for one regression (Table 9, Appendix III). In the altered interest rate specification, AI's estimated impact remains insignificant at the 5% level for both unemployment and job vacancies. The labor market slack model with both countries and regions turns significant at the 5% level, but the R^2 worsens. This means that the original model better explains the variation. Furthermore, the long-term interest rate is insignificant across all regressions, suggesting that it has a low explanatory value.

Substituting the general education variable with tertiary education (Table 10, Appendix III) produced similar results: both the unemployment and job vacancies regression are insignificant across all regressions. However, AI adoption's effect on labor market slack at the regional level becomes insignificant when tertiary education is used instead of general education. This may reflect that tertiary education more accurately captures the middle-income jobs, which are most exposed to AI. Nonetheless, this regression has a lower R-squared than the regression in Table 3, suggesting that the original model better explains the variation in the model.

Since inflation and short-term interest rates are strongly correlated and may significantly impact results, an additional regression is performed where inflation is omitted (see Table 11, Appendix III). This model specification causes all regressions to become insignificant at the 5% level. However, multicollinearity concerns should be alleviated since the standard errors remain similar even if inflation is excluded. The exclusion of the variable also reduces the R^2, suggesting that inflation has some explanatory value and should be included.

Finally, the AI usage rate was lagged by one year (Table 12, Appendix III), although data availability limits this approach. When lagged, the variable remains insignificant for all the different regression models. This could either reflect data limitations or that there is no causal relationship. However, other causality tests support a unidirectional relationship between AI and low-skill employment (See 5.1.5), indicating that the lack of data is potentially the reason for not finding any significant result. Moreover, lagged AI regressions include observations from 2022 – which were excluded in the original regression. As such, the lagged regression also tests whether the results were due to spurious correlations. Regardless, the short time frame and omitted variables limit the ability to draw causal inferences from the lagged models.

To conclude, the AI variable remains statistically insignificant across all robustness checks for Models 1 and 2, strengthening the conclusion that AI's impact on the two aspects of the Beveridge curve – job vacancies and unemployment – is empirically ambiguous. However, the significance of the AI variable in Model 3.2 varies across the various robustness checks – with one of the regressions indicating that AI has a significant negative effect on labor market slack, and the other three regressions showing insignificant results for the AI variable. This suggests that even though Model 3.2 in Table 3 is to be considered the most correct model for interpreting the impact of AI adoption on labor market slack, the results are not particularly robust and must be interpreted with caution. The underlying endogeneity concerns means that we can at most make correlational claims regarding AI's impact on the European labor market's matching efficiency.

7. Discussion

7.1. Main Findings

This thesis contributes to a growing body of literature on AI and European labor markets. Regression results suggest there is no significant correlation between matching efficiency and AI usage, implying that AI adoption does not appear to be related to a shift in the Beveridge curve. In other words, the production gains from AI usage will likely not come at the cost of worsened labor market matching efficiency. Moreover, there is a negative correlation between labor market slack and AI usage at the more robust regional level. This suggests that broader improvements in matching are correlated with AI usage.

Furthermore, industry heterogeneity was observed. The correlation between job vacancies and AI usage differs across industries, although data limitations introduce some uncertainty. Notably, the information and communication industry's job vacancy rate is negatively correlated with AI according to our regression, suggesting greater capabilities to fill positions. This corresponds to a downward shift of the Beveridge curve, which in turn would correspond to an improvement in matching efficiency (See Figure 11). However, since the industry-specific change in unemployment is unknown, the overall change in matching efficiency remains uncertain.

The findings suggests that countries may benefit differently from AI in labor market matching depending on industry composition, which aligns with the theoretical framework (Section 3.3). Why the information and communication industry seemingly benefits more from AI usage could be because the industry is actively developing AI. This means that the skill mismatch-effect should be reduced for the information industry since developers will have a more extensive in-depth knowledge of AI usage.

Figure 11. How increased AI usage in the information industry correlates with the Beveridge curve. Source: (Beggs (2019). "The Beveridge Curve". *ThoughtCO*. https://www.thoughtco.com/overview-of-the-beveridge-curve-1148116 (Retrieved 2025-05-08). Modified.)

The relationship between matching efficiency and AI found differs from previous literature by Wiles and Horton (2025), who found a negative relationship between AI and matching efficiency. This is likely due to them focusing on one aspect of AI and matching efficiency, while our regression captures the total net effect. Guarascio et al. (2025) found a positive relationship between employment and AI – we find no such relationship. This is likely due to recent advances in AI, which makes older datasets incomparable to the newer. It could also be due to the shorter time-series used in the analysis.

7.2. Strengths and Shortcomings of the Model

The primary weakness of the model lies in the restricted data availability, especially in terms of the time series length. This creates issues with imputations, omitted variables and the lack of causal inference tools and tests (e.g. Granger Causality test or IV regressions). As such, there are concerns regarding internal validity and no causal claims can be made with certainty.

Despite these limitations, the thesis provides an early foundation for understanding AI's relationship with matching efficiency. Once data becomes available in the future, it will be possible to perform more causality tests. Additional data will also mitigate imputation limitations and potentially reduce bias in the dataset.

Moreover, structural differences between countries such as Denmark and Spain highlight a challenge to generalize results. It has been attempted to show industry heterogeneity, but the availability of data makes it difficult to draw any strong conclusions. While heterogeneity was only partially addressed, the thesis still identifies important future research – sector-specific AI-usage.

Although there are some recent studies on employment and artificial intelligence, the relationship between AI and job vacancies lacks research. Furthermore, it is not reasonable to assume that the relationship between AI and matching efficiency remains the same over time. Using data from the 2010s to predict current effects could be questioned. Therefore, the model brings forth and highlights new information. As additional data becomes available it would be interesting to further investigate each respective industry from Eurostat, which could highlight which industries' job vacancies are correlated with negative AI usage.

7.3. Policy Implications

Findings suggest that implementation of AI is not associated with reduced matching efficiency. In fact, AI usage is correlated with a decrease in labor market slack, which incorporates a wider workforce than unemployment. Therefore, if policymakers are concerned of potential matching inefficiencies because of AI usage, this thesis provides initial reassurance that no such correlation exists. If anything, the negative relationship between AI and labor market slack highlights positive matching outcomes. In countries with low adoption rates, this suggests that there is an opportunity to pursue productivity gains without compromising the matching process.

These results are in line with macroeconomic arguments which suggest that mass technological unemployment due to AI is an unlikely proposition. Technology is a deflationary force which drives down costs and prices. This pushes up the consumers' real income and aggregate demand which in turn leads to new employment. These results cannot be seen for AI in this analysis, but the potential replacement of labor by AI is likely to lead to a gradual and cumulatively significant cost reduction and in turn, productivity growth. However, to ensure that AI becomes deflationary and has a positive impact on employment, cost reduction must translate into lower prices. To achieve this outcome, it is essential that policymakers ensure a competitive market structure (Carlsson-Szlezak & Swartz, 2024).

Furthermore, it is crucial that adoption is pursued in the correct context; the fundamental factors must be in place for AI to work. If so, there seems to be no side effects to the matching quality when adopting. As such, it is interesting to understand and investigate which contexts are successful. What can be learnt from adoption leaders that cause them to have a high usage rate? Are there patterns among the countries with the most AI usage?

Additionally, it is interesting to investigate why certain industries gain more than others. As mentioned in the main findings, the information and communication industry – which is actively using and developing AI – gains more from the usage of AI than others. Could this be due to more extensive knowledge and better digital literacy within the industry?

The adoption leader Denmark, for instance, has actively invested in digital infrastructure, data governance and close public-private collaborations over the last two decades. The country has adopted a 'digital-by-default' mindset, ensuring that citizens are able and ready to adopt new digital technology (Ministry of Foreign Affairs of Denmark, 2025). This makes it easier for companies to adopt and use AI – which correlates with increased matching efficiency. The industries with the most employed in Denmark according to Statistics Denmark (n.d.) are 'public administration, education and health', 'trade and transport' and 'manufacturing'. Additionally, both the information and finance sector have a substantial number of employees. This might be a composition of a structural economy that easily adopts AI.

The second largest adopter, Sweden, also emphasizes collaboration between the public and private sectors. The start-ups using AI must be supported by the industry at large as well as the government and its research institutions. The scientific institutions in Sweden are crucial for its AI development strategy as they help support businesses through close collaborations. As such, the usage and development of AI must be developed cross-sectionally (Business, Sweden n.d.). As such, the government must play a central role in fostering AI usage and innovation.

Investing heavily in digital skills and infrastructure such as Denmark could help bridge gaps in AI adoption. As Guarascio et al. (2025) also notes, there is a 'context-dependent' nature of AI. Thus, policies mimicking adoption leaders may prove useful for the countries with low AI usage, assuming that the major industries and occupations within the countries are similar. Increasing collaborations across industries could improve both AI knowledge and digital literacy, which seem to be key to ensuring an unchanged matching process. An increased investment in digital literacy and AI knowledge could perhaps even correlate with an improved matching quality overall, as is likely the case for the information industry.

Lastly, the findings indicate that broader and nuanced measurements of matching efficiency and general labor markets are required to estimate the true relationship with AI. By incorporating a broader labor force, we found a significant relationship with AI – suggesting that individuals outside the traditional labor force are more strongly impacted by an increased AI usage, all else equal. This means that policymakers may need to look beyond traditional labor market metrics such as unemployment to uncover the true impact of AI.

7.4. Future Research

As mentioned briefly above, AI's impact and relationship with matching efficiency is largely unexplored. This thesis opens new research possibilities as the relationship between matching efficiency and AI is still a new subject. Due to the data limitations mentioned above, the study had to be conducted for the entirety of Europe, which does not provide extensive results for country- or industry heterogeneities. As such, the more focused studies can be conducted using a practically identical Eurostat dataset as it becomes available.

In addition, if a valid IV-instrument is found another study could provide better causal claims than this thesis. The same could be said for the Granger causality test as more data becomes available. This would improve the robustness of the results found in the thesis. As AI is a new and hotly debated issue, there is a plethora of different labor market studies available to be tested. For instance, by building the estimation strategy on the Search theory (Gottfries, 2013) instead of the Beveridge curve allows a new dimension of AI and labor market to be investigated. The different channels through which AI impacts matching efficiency could also be investigated further. For instance, it would be interesting to investigate the different labor market policies' relationship with AI further.

8. Conclusion

This paper investigates the relationship between artificial intelligence and labor market matching efficiency to understand how the current boom in AI may affect labor market dynamics. We use national and regional panel data from European countries for the years 2021, 2023, and 2024 to analyze the macroeconomic effects of AI adoption. Using the theoretical framework of the Beveridge curve, we estimate fixed effects regressions on unemployment and job vacancies to assess whether AI usage is associated with a shift in the curve – and thus, a change in matching efficiency. Fixed effects regressions are also run on labor market slack to provide a more complete picture of the labor market. Finally, the relationship between AI and job vacancies across four sectors with low and high exposure to AI respectively is explored to examine potential heterogeneity across industries.

When estimating the impact on the Beveridge curve, no statistically significant relationship between AI usage and either unemployment or job vacancies is found. Therefore, it cannot be concluded that a change in AI usage influences matching efficiency via the Beveridge curve framework. However, there is a statistically significant and negative relationship between artificial intelligence and labor market slack – indicating a positive relationship between AI adoption and matching efficiency. The results suggest an elasticity of approximately -0.05, implying that effects may be economically significant in regions with high labor market slack and low AI adoption rate.

By industries, the results are statistically insignificant across all industries except for the information and communication sector, where an elasticity of approximately -0.29 between job vacancies and AI usage is estimated. As the information and communication sector is the industry with the highest usage of AI in our sample, our findings suggest that the effects of AI are heterogeneous and more pronounced in industries with greater AI exposure.

Overall, the findings suggest that the relationship between AI adoption and labor market matching efficiency is ambiguous, though there is some evidence of a positive relationship. Additionally, the effects appear to be heterogeneous across industries. However, these results should be interpreted with caution. Due to a limited amount of data and a short time series, there are concerns regarding internal validity and causal claims. The results found are only correlational.

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Appendices

Appendix I – Descriptive statistics and data visualization

Calculations for the job vacancy rate

The total number of job vacancies for Austria and Spain was combined with Eurostat's employment data to calculate the job vacancy rate with the following equation:

$$Job\ vacancy\ rate_{it} = \frac{Number\ of\ job\ vacancies_{it}}{Number\ of\ job\ vacancies_{it} + Number\ of\ Employments_{it}} * 100$$

The actual formula for the job vacancy rate uses the number of occupied job posts instead of the number of employments. However, data was unavailable for occupied job posts. Therefore, we decided to use the closest measurement that we could find NUTS 2 data on – the number of employments. The number of employments and occupied job posts will likely differ because one person can have multiple jobs, thus counting as one employee, but also counting for multiple occupied job posts.

To check that the measure was not too different from the actual job vacancy rate measure, we looked at the national level of Austria and Spain and compared our measure with Eurostat's measure. A comparison between the calculated job vacancy rate and Eurostat's job vacancy rate is displayed in Table 5. Unexpectedly, the values from our calculations are lower than the corresponding Eurostat values. If one individual can have multiple jobs, occupied jobs should be higher than employment and therefore, Eurostat's rate should be lower than ours. The reason that our values are lower is likely to be due to differences in definitions or sectors included, but this is not a problem for our analysis. Since a fixed effect panel data regression is used, what matters is the difference from year-to-year within each entity. As the table also displays, the year-to-year difference is very similar between the two measurements for both Austria and Spain. However, the difference in calculations must be considered when interpreting the results.

Table 5. Our job vacancy rate measurement vs. Eurostat's job vacancy rate

Austria	2021	2022	2023	2024
Our calculated job vacancy rate	2,16	2,75	2,36	1,98
Eurostat's job vacancy tate	3,85	5,30	4,70	3,98
Spain	2021	2022	2023	2024
Our calculated job vacancy rate	0,56	0,68	0,69	0,69
Eurostat's job vacancy rate	0,75	0,90	0,88	0,90

Figure 22 and 23 in Appendix I show the difference in relationship between AI and job vacancy rate for observations with our job vacancy rate calculation and Eurostat's measure. Figure 22 includes all observations that use our job vacancy rate calculation for the years 2021, 2023, and 2024, and Figure 23 includes all regional observations for Eurostat's measurement between the same years. As visible, the trendline between the two variables for our calculated vacancy rate has a less steep trendline than the plot with observations with Eurostat's measure.

Calculations for real GDP, real GDP growth and population change

Following the method for constructing real GDP outlined in Macroeconomics by *Olivier Blanchard* (2020), real GDP was calculated with the following equations:

$$Index_{it} = Index_{i,t-1} * (1 + Rate\ of\ change_{it})$$

$$Real\ GDP_{it} = \frac{Nominal\ GDP_{it}}{Index_{it}}$$

The inflation rate is used as the rate of change in the price level. The year 2019 is set as the base year, meaning the index is normalized to 1 this year. For each of the following years the previous year's index is multiplied by the inflation factor. Finally, nominal GDP is deflated by this index, providing a measure of real GDP, chained in 2019 euros.

Additionally, real GDP growth and population change have been calculated using the constructed real GDP measure and the variable for population data from Eurostat. Both variables represent the annual percentage change. The following formulas were used:

$$Real\ GDP\ growth_{it} = \left(\frac{Real\ GDP_{it} - Real\ GDP_{i,t-1}}{Real\ GDP_{i,t-1}}\right) \times 100$$

$$Population\ change_{it} = \left(\frac{Total\ population_{it} - Total\ population_{i,t-1}}{Total\ population_{i,t-1}}\right) \times 100$$

Explaining the data – figures and tables

Table 6. List of countries and NUTS 2 regions included in the final regressions.

Countries	AT, BE, BG, CZ, DE, DK, EE, EL, ES, FI, FR, HU, IE, IT, LT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK
Regions	AT11, AT12, AT13, AT21, AT22, AT31, AT32, AT33, AT34, BG31, BG32, BG33, BG41, BG42, DK01, DK02, DK03, DK04, DK05, ES11, ES12, ES13, ES21, ES22, ES23, ES24, ES41, ES42, ES43, ES51, ES52, ES53, ES61, ES62, HU21, HU22, HU23, HU31, HU32, HU33, RO11, RO12, RO22, RO31, RO32, RO41, RO42

Table 7. List of variables

Variable	Definition	Source
AI	Percentage of enterprises using artificial intelligence	Eurostat
Unemployment rate	Share of unemployed people in the labor force	Eurostat
Job vacancy rate	Share of job vacancies relative to the total number of job posts - filled and vacant	Eurostat, Statistics Denmark, Statistics Austria*, Instituto Nacional de Estadística*
Labor market slack	Share of labor market slack in the extended labor force	Eurostat
GDP	Gross Domestic Product at market prices – current prices (million EUR)	Eurostat
Population	Total population	Eurostat
Education	Share of population aged 25–64 with upper secondary, post-secondary, non-tertiary or tertiary education (levels 3-8)	Eurostat
Tertiary education	Share of population aged 25–64 with tertiary education (levels 5-8)	Eurostat
Long-term interest rate	Estimated closing yields on 10-year Commonwealth treasury bonds	OECD
Short-term interest rate	Bank accepted bills/negotiable certificates of deposit-3 months	OECD
Real GDP	Real Gross Domestic Product – constant prices (deflated using HICP, base year 2019, million EUR)	Eurostat*
Real GDP growth	Annual growth rate of real GDP – percentage change from previous year	Eurostat*
Population change	Annual growth rate of total population – percentage change from previous year	Eurostat*
Inflation	HICP inflation rate - annual average rate of change	Eurostat
High-tech sector	Share of total employment in high-technology sectors	Eurostat

Note: * indicates own calculations based on the data source provided in the table.

Table 8. Descriptive statistics for each sector

Variable	Observations	Mean	Std. Dev.	Min	Max
Administrative and Support Services					
AI	232	9.67	7.28	0.27	40.31
	(232)	(1.95)	(0.90)	(-1.31)	(3.70)
Job vacancy rate	111	2.95	3.12	0.10	15.75
	(111)	(0.51)	(1.15)	(-2.30)	(2.76)
Information and Communication					
AI	238	35.43	18.33	1.56	90.48
	(238)	(3.38)	(0.69)	(0.44)	(4.51)
Job vacancy rate	118	1.95	1.76	0.10	7.65
	(118)	0.23	0.98	-2.30	2.03
Construction					
AI	231	4.65	3.72	0.09	19.08
	(231)	(1.03)	(1.28)	(-2.41)	(2.95)
Job vacancy rate	116	1.95	1.91	0.08	8.05
	(116)	(1.48)	(1.11)	(-2.59)	(2.09)
Manucaturing					
AI	245	8.93	6.41	0.13	27.13
	(245)	(1.86)	(0.95)	(-2.04)	(3.30)
Job vacancy rate	120	1.62	0.99	0.30	4.33
	(120)	(0.29)	(0.64)	(-1.20)	(1.46)

The table presents descriptive statistics for AI adoption and job vacancy rate in 2023 and 2024 for the sectors used to check for heterogeneity in Model 4. Log-transformations are in parentheses.

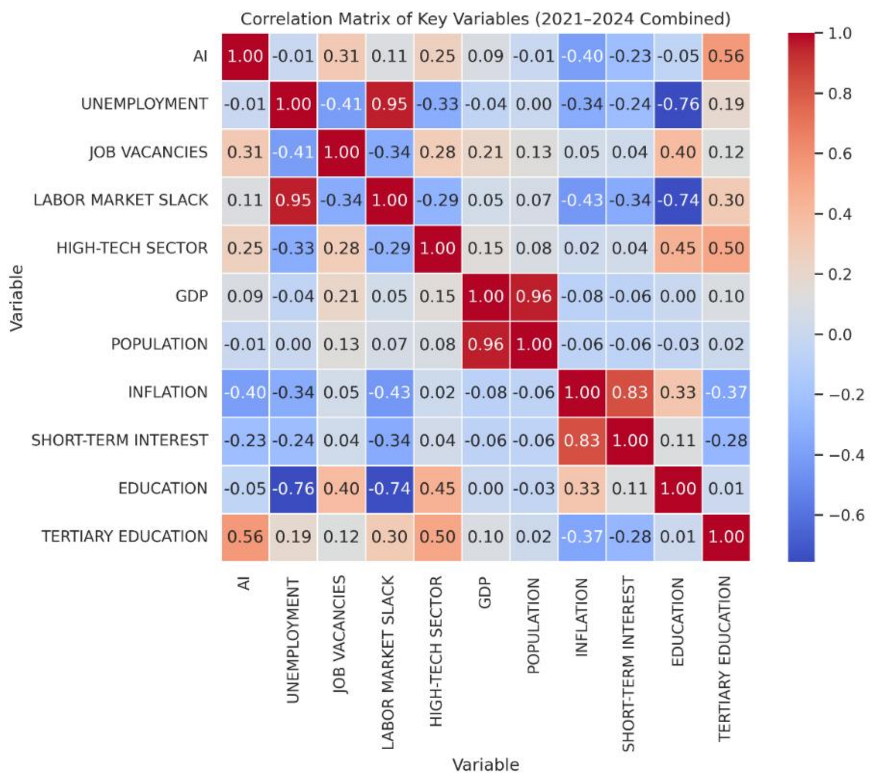
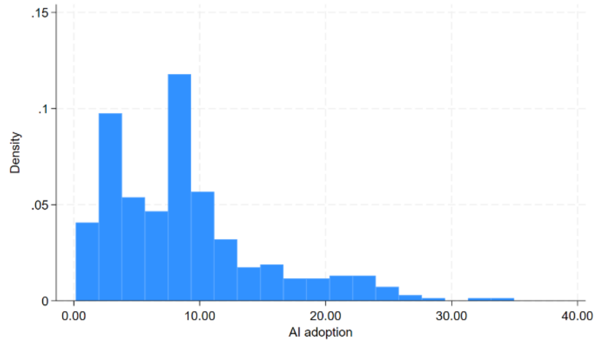


Figure 13. Heat map correlation matrix of all base variable. (Observations in 2022 are not included in this matrix)



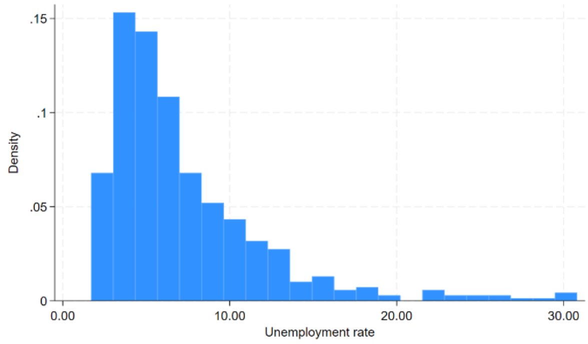
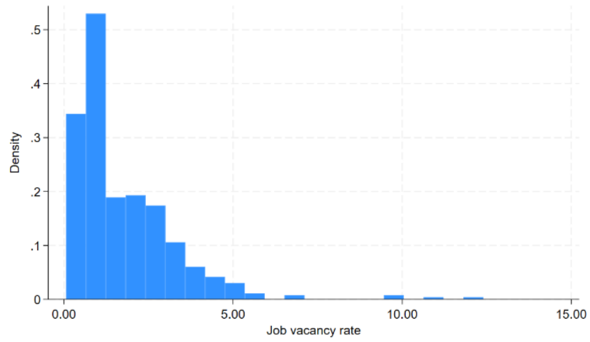


Figure 14. Distribution of AI adoption. Skewness = 1.27

Figure 15. Distribution of unemployment. Skewness = 2.08



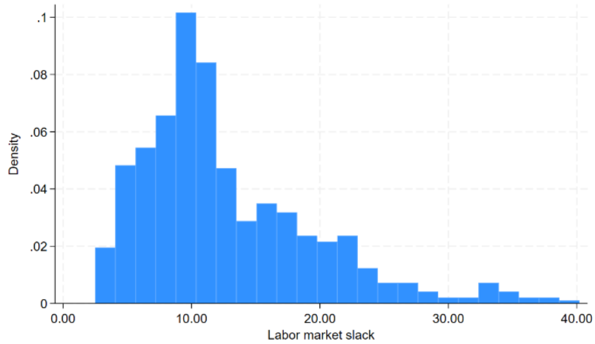


Figure 16. Distribution of job vacancy rate. Skewness = 2.5

Figure 17. Distribution of labor market slack. Skewness = 1.26

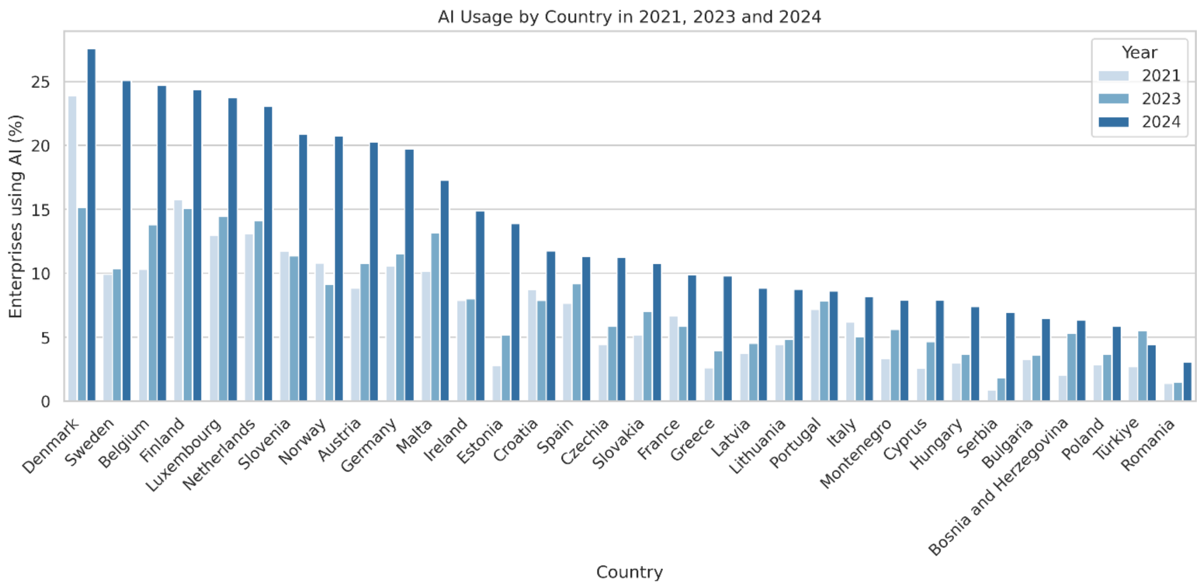


Figure 18. Share of enterprises that use AI per country. Including the years 2021, 2023 and 2024.

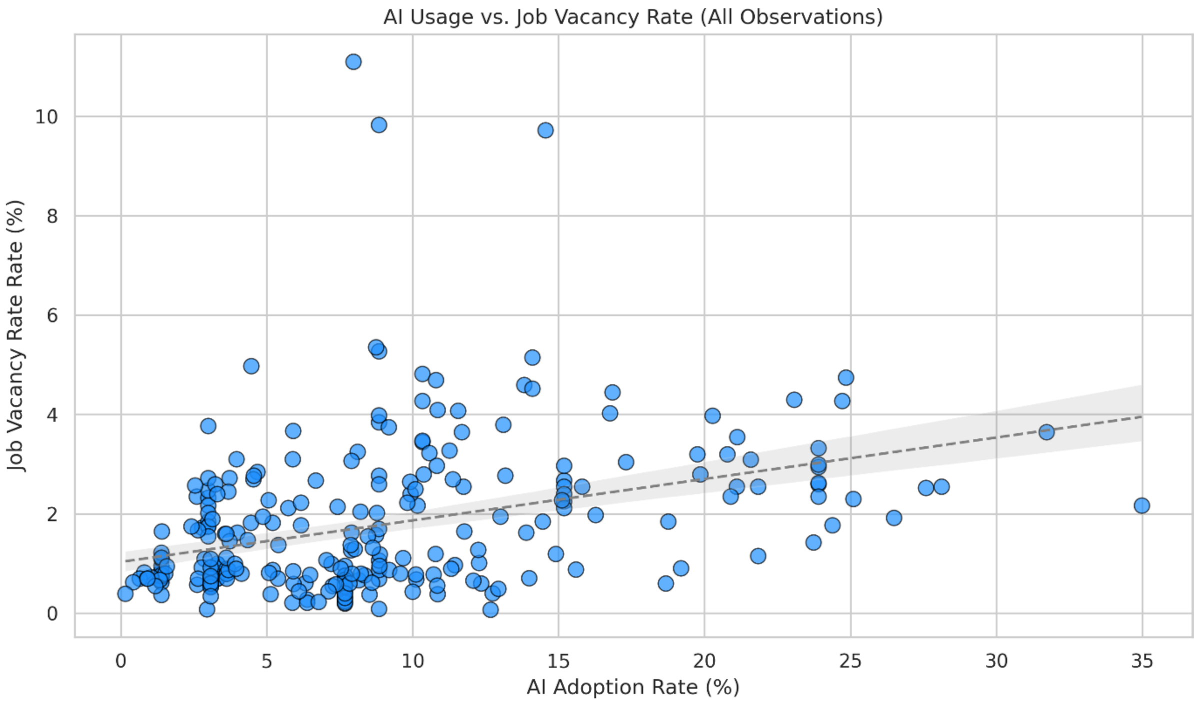


Figure 19. Scatterplot between AI usage and job vacancy rate. 270 observations, correlation = 0.366, p-value = 0.000.

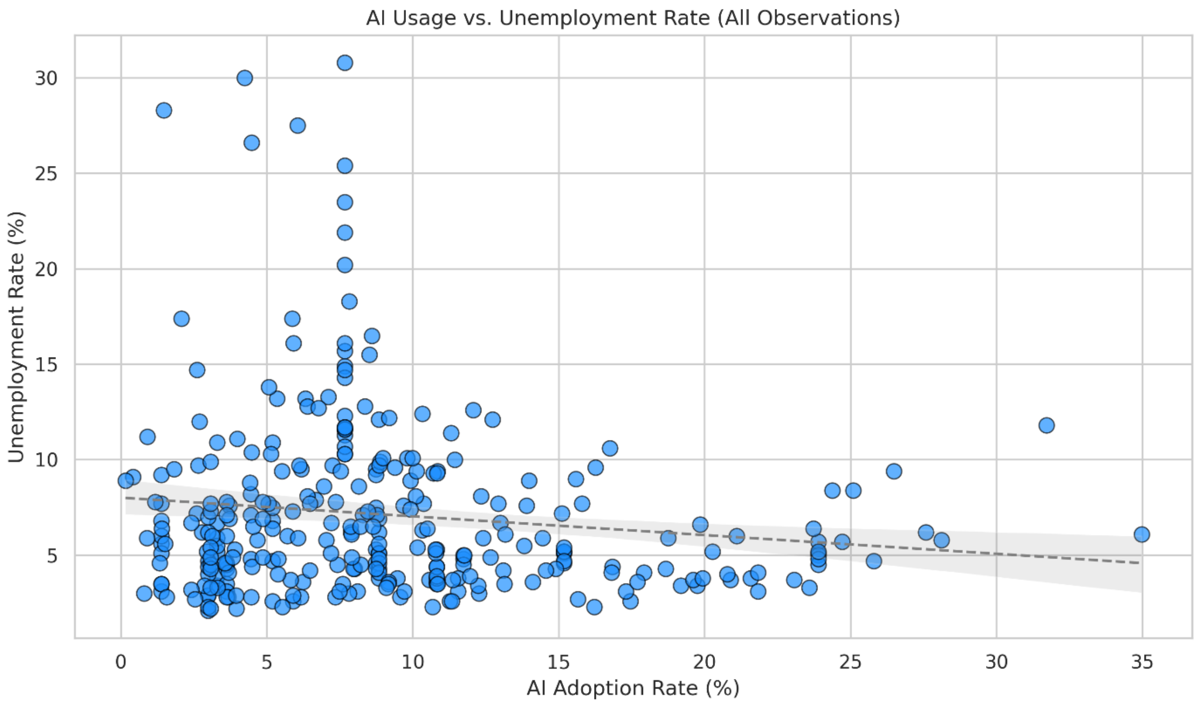


Figure 20. Scatterplot between AI usage and unemployment rate. 314 observations, correlation = -0.132, p-value = 0.020.

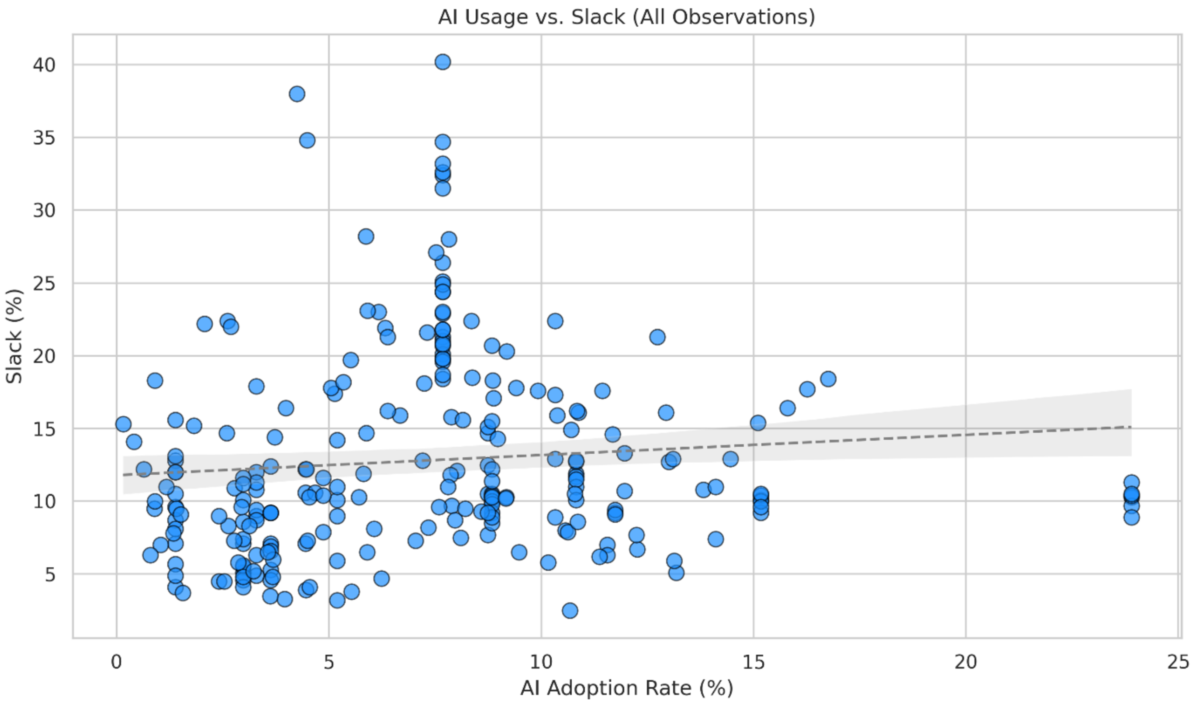
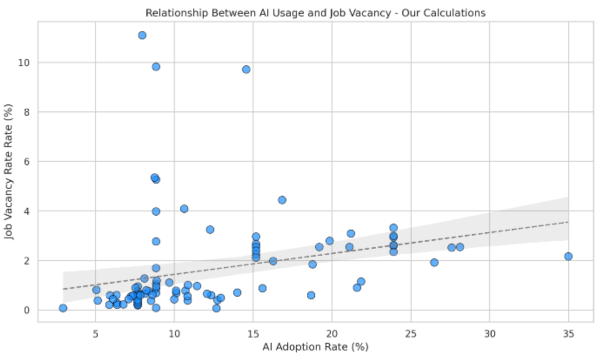


Figure 21. Scatterplot between AI usage and labor market slack. 372 observations, correlation = 0.013, p-value = 0.802.



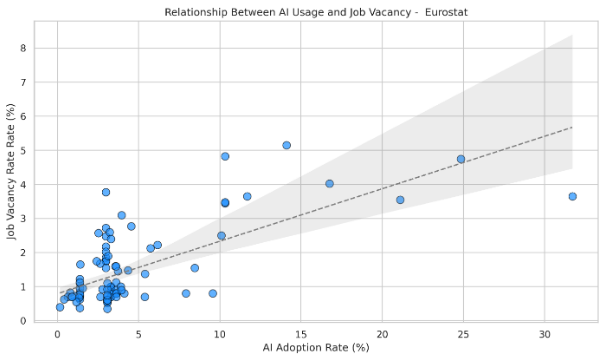


Figure 22. Observations with our calculation for job vacancy rate

Figure 23. Observations with Eurostat's job vacancy rate

Appendix II – Explanation of control variables

Business Cycles

The real GDP does not grow at a constant rate; there are periods of high growth followed by periods of low growth or even decline. Therefore, economists frequently make a distinction between trend- and cyclical components when explaining growth. The main idea is that the trend component represents the permanent changes in GDP – the cyclical component instead represents a temporary, brief change. Permanent changes in the GDP may be due to changes in technology, capital stock, labor force participation as well as the natural level of unemployment. Cyclical fluctuations on the other hand may be due to demand shocks which cause production to deviate from the natural level. It may also be due to temporary changes in the production possibilities; even a structural change – such as a technological change – may lead to a brief change in the natural level of production. Furthermore, production is not the sole part of the economy exposed to the cyclical nature of growth; consumption, employment and investment also fluctuate (Gottfries, 2013). Thus, when measuring the impact of AI on labor market outcomes, it is crucial to distinguish between structural transformations driven by technological progress and temporary business cycles.

The IS-LM framework provides four interconnected equations that can be used to adequately describe business cycles fluctuation and equilibrium the goods- and money market:

(1) Goods market equilibrium: $Y = I + C$
(2) Consumption function: $C = C(Y, Y^e, i - \pi^e, A)$
(3) Investment Function: $I = I(\ i - \pi^e, Y^e, K)$
(4) Money Market equilibrium: $\frac{M}{P} = \frac{Y}{V(i)}$

The IS curve represents different equilibriums in the goods market (1), holding all except production (Y) and interest rate (i) constant. It is determined by underlying consumption (C) and investment (I) functions. As shown in the equations above, these two variables are in turn determined by the interest rate (i), expected inflation (π^e), output (Y), expected output (Y^e), capital (K) as well as wealth (A). The IS curve is downwards sloping as an increase in interest rate has a negative effect on both investment and consumption. When other exogenous variables (shocks) in the I or C functions change, the IS curve will shift.

The LM curve represents the money market equilibrium, where real money supply ($\frac{M}{P}$), the output (Y) and the velocity of money (V) determines the interest rate. The curve holds all except interest and output constant in the same way as the IS curve does. Thus, it shows the interest rate in the money market at a given level of production, holding the real money supply constant. The curve slopes upwards as higher production leads to a lower willingness to borrow and a higher demand for cash; as such, the interest rate will rise along with output. Increases in the money supply (M) or decreases in the price level (P), will shift the curve downwards.

The two curves are combined with production on the horizontal axis and interest rate on the vertical axis. The markets are in equilibrium where the two curves intersect. Together, they aim to explain how macroeconomic variables respond to demand- and policy shocks as well as other disturbances in the short-run; impacts on the goods market or money market will shift where the two curves intersect, consequentially impacting the general equilibrium between the two different markets. (Gottfries, 2013). As such, the framework provides valuable insights into what macroeconomic and regional variables to control for in short-run regressions.

A concern with estimating macroeconomic effects is the lagged effects of changes in the short-run. Using a vector autoregressive (VAR) model, it has been shown that the total effect of a policy takes time. For instance, inflation tends to respond quite sluggishly to a policy choice, and so does interest rates as well as GDP. As such, the true impacts of an exogenous shock or policy choice take time to impact the total economy (Gottfries, 2013).

As central banks control the short-term interest rate and not the long-term or medium-term interest rates (Sveriges Riksbank, n.d.), it is the natural control for the IS-LM model's interest rate. Why long-term interest rates could be chosen instead of short-term interest rates can be attributed to capital investments in artificial intelligence being long-term. These investments should not be dependent on short-term fluctuations. A straightforward way to test robustness of the short-term interest rate control could be by simply changing to a long-term interest rate control variable; if overall regression results differ, the robustness of the results could be questioned.

Unemployment and Inflation

Unemployment rates may be higher or lower than the natural rate in the short run. These short-run deviations are called cyclical unemployment and can be interpreted with two versions of the *Phillips curve.* The first version of the Phillips curve illustrates the relationship between unemployment and the rate of wage inflation. It builds on the wage-setting equation and assumes that firms have completely flexible wages or rigid wages, which are set based on the expected wage and unemployment levels. The weighted average of the rigid wage and the flexible wage is the expected wage level. According to this model, if unemployment is at its natural level, wages will rise in line with expectations.

The second version of the Phillips curve illustrates the relationship between unemployment and price inflation. It suggests inflation depends on expected inflation, unemployment and unexpected changes in productivity. This version implies that as unemployment falls below the natural rate, inflation tends to increase. (Gottfries, 2013)

Population and Labor Markets

According to Gottfries (2013), long-term growth is determined partially by population growth. Since capital per worker depends on population growth in the Solow Model, greater capital deepening is required to compensate for increased population growth. As such, the marginal product of labor will decrease if there is not adequate capital to complement the recent additions to the labor force, making capital potentially more favorable than labor. At the same time unemployment can be expected to increase if created work opportunities are unable to keep up with population growth. If there is a growing working-age population with inadequate supply of job vacancies, the working age population increase will constitute an increase in unemployment and greater difficulties for new labor market entrants (ILO, n.d.). Thus, both job vacancies and unemployment will be impacted by population growth.

Human Capital and Education

Human capital is both an end and a means of economic development; it contributes to GDP growth. A typical way to measure human capital is through education; since education is the easiest way to estimate human capital, it is also the most widely studied and used metric. Although there is simultaneity in the causal relationship between education and growth, it has been established though a plethora of studies that it is most likely of the first-order importance in determining GDP (De Janvry & Sadoulet, 2021). For instance, in the Solow Model, education is used to account for differences in human capital when estimating GDP. In the productivity-adjusted labor force – where differences in human capital are accounted for – the productivity of labor depends on the years of schooling and its coefficient, estimated to be 10% (Gottfries, 2013). The Solow model's technology variable also requires an adequate level of education to adopt and use innovative technology. Thus, structural economics, and in turn labor markets are correlated with education levels.

Therefore, to be at the forefront of the technological frontier and in turn GDP per capita, education is essential (De Janvry & Sadoulet, 2021). There is also a relationship between AI adoption and education level; individuals with a higher education level show a higher level of trust towards AI-powered recommendations (Biswas & Murray, 2024). This contributes to existing economic literature and previously mentioned model, where the education level determines the degree of advanced technologies used. Therefore, countries with higher education levels would be more prone to adopt AI; the exposure to AI should be higher. As such, it is essential to improve education and other human capital dimensions. The income of an individual is directly determined by levels of human capital on the micro-level. A higher education corresponds to an average higher wage, just as better health corresponds to better wages. (De Janvry & Sadoulet, 2021).

Education Controls

Chosen variable to proxy level of education is the share of population aged 25 - 64 with upper secondary, post-secondary, non-tertiary or tertiary education, measured in percent. There are natural flaws with educational measurement. For instance, it does not consider individuals below the age of 25 who are part of the labor force; Eurostat does not provide a measurement for all ages. Choosing tertiary education rate as the control instead may mitigate the omission of younger labor, since completion of tertiary schooling occurs later in life. It could be argued that tertiary education is a better control in the case of AI usage; higher education is positively correlated with AI usage rates. However, the correlation between AI and tertiary education can potentially introduce multicollinearity in the model if included. As such, the tertiary education rate is only used as a robustness check control variable.

Still, omission of the younger population remains a concern – some of whom are of working age and partaking in the labor market. Additionally, the distribution is unknown. So, if education levels between individuals differ greatly within the region, the variable will not represent a valid proxy. As it is a composite measure, the proxy for general education level does not show how the different educational attainment levels are distributed. As such, robustness checks will be conducted to validate the proxy variable for education. By changing the proxy to measure only the tertiary education rate will suffice for investigating the robustness of the education control.

Appendix III – Tables for robustness checks

Table 9. Robustness check – replacing short-term interest rate with long-term interest rate.

VARIABLES	(1.1) UNEMPLOY-MENT RATE (All)	(1.2) UNEMPLOY-MENT RATE (Regions)	(2.1) VACANCY RATE (All)	(1.2) VACANCY RATE (Regions)	(3.1) LABOR MARKET SLACK (All)	(3.2) LABOR MARKET SLACK (Regions)
ln AI	**-0.033**	**-0.032**	**-0.027**	**-0.077***	**-0.061****	**-0.056****
	(0.029)	(0.032)	(0.053)	(0.044)	(0.027)	(0.025)
Lagged ln unemployment			-0.193	-0.072		
			(0.142)	(0.122)		
Lagged ln vacancy rate	-0.159***	-0.108			-0.142**	-0.018
	(0.054)	(0.087)			(0.060)	(0.070)
Population rate	-0.020	-0.102**	-0.004	0.108*	0.031	-0.086**
	(0.015)	(0.040)	(0.032)	(0.054)	(0.031)	(0.035)
Lagged long-term interest	0.042**	0.043	-0.032	0.001	-0.001	-0.011
	(0.020)	(0.026)	(0.022)	(0.028)	(0.013)	(0.018)
Lagged real GDP growth	-0.006***	-0.007***	0.010**	0.014***	-0.004**	-0.005**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)
Inflation	-0.008*	-0.012**	0.009	0.008	-0.005*	-0.006*
	(0.004)	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)
Education	-0.025***	-0.038***	0.026	0.021	-0.027***	-0.037***
	(0.009)	(0.011)	(0.017)	(0.019)	(0.009)	(0.010)
High-tech sector	0.012	-0.001	-0.004	0.011	-0.017	-0.009
	(0.031)	(0.039)	(0.044)	(0.047)	(0.031)	(0.027)
2023	-0.062	-0.004	-0.001	-0.199*	-0.039	0.013
	(0.051)	(0.073)	(0.069)	(0.100)	(0.043)	(0.064)
2024	-0.123	-0.067	0.027	-0.155	-0.008	0.042
	(0.086)	(0.118)	(0.085)	(0.119)	(0.071)	(0.099)
Constant	3.788***	4.772***	-1.332	-1.382	4.797***	5.456***
	(0.732)	(0.837)	(1.257)	(1.400)	(0.734)	(0.810)
Observations	226	143	226	143	226	143
R-squared	0.417	0.439	0.180	0.231	0.496	0.553
Number of spatial units	76	48	76	48	76	48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the results for one of the robustness checks for the regressions models in Table 2. The model names in this table corresponds to the same model names in Table 2. As a robustness check, the control variable short-term interest rate is replaced with long-term interest rate in these regressions.

Table 10. Robustness check – replacing general education with tertiary education

VARIABLES	(1.1) UNEMPLOY-MENT RATE (All)	(1.2) UNEMPLOY-MENT RATE (Regions)	(2.1) VACANCY RATE (All)	(2.2) VACANCY RATE (Regions)	(3.1) LABOR MARKET SLACK (All)	(3.2) LABOR MARKET SLACK (Regions)
ln AI	**-0.025**	**-0.028**	**-0.031**	**-0.078***	**-0.038**	**-0.042***
	(0.030)	(0.032)	(0.052)	(0.044)	(0.028)	(0.024)
Lagged ln unemployment			-0.166	-0.059		
			(0.148)	(0.122)		
Lagged ln vacancy rate	-0.143**	-0.066			-0.120*	0.024
	(0.058)	(0.086)			(0.069)	(0.081)
Population change	-0.031*	-0.032	0.005	0.074	0.036	-0.040
	(0.016)	(0.037)	(0.042)	(0.055)	(0.034)	(0.039)
Lagged short-term interest	0.026***	0.030***	-0.013	-0.007	0.010**	0.006
	(0.006)	(0.007)	(0.009)	(0.010)	(0.005)	(0.006)
Lagged real GDP growth	-0.007***	-0.010***	0.011***	0.016***	-0.005***	-0.006***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)
Inflation	-0.009***	-0.012***	0.009*	0.010*	-0.008***	-0.008***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)
Tertiary education	-0.014	-0.016**	0.007	0.019	-0.010	-0.019**
	(0.009)	(0.007)	(0.012)	(0.015)	(0.010)	(0.009)
High-tech sector	0.023	0.004	-0.005	0.001	0.000	-0.004
	(0.033)	(0.038)	(0.042)	(0.042)	(0.028)	(0.027)
2023	-0.011	-0.020	-0.046	-0.178**	-0.072*	-0.056
	(0.045)	(0.046)	(0.059)	(0.087)	(0.038)	(0.047)
2024	-0.098*	-0.099	-0.009	-0.121	-0.092	-0.057
	(0.055)	(0.064)	(0.069)	(0.092)	(0.061)	(0.069)
Constant	2.284***	2.398***	0.364	-0.332	2.863***	3.187***
	(0.288)	(0.261)	(0.471)	(0.499)	(0.354)	(0.269)
Observations	221	143	221	143	221	143
R-squared	0.441	0.476	0.163	0.236	0.449	0.492
Number of spatial units	74	48	74	48	74	48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the results for one of the robustness checks for the regressions models in Table 2. The model names in this table corresponds to the same model names in Table 2. As a robustness check, the education control variable is replaced with tertiary education in these regressions.

Table 11. Robustness check – excluding inflation.

	(1.1)	(1.2)	(2.1)	(2.2)	(3.1)	(3.2)
VARIABLES	UNEMPLOY-MENT RATE (All)	UNEMPLOY-MENT RATE (Regions)	VACANCY RATE (All)	VACANCY RATE (Regions)	LABOR MARKET SLACK (All)	LABOR MARKET SLACK (Regions)
Ln AI	**-0.026**	**-0.030**	**-0.025**	**-0.085***	**-0.043**	**-0.045***
	(0.030)	(0.032)	(0.053)	(0.044)	(0.026)	(0.024)
Lagged ln unemployment			-0.179	-0.077		
			(0.148)	(0.122)		
Lagged ln vacancy rate	-0.132***	-0.085			-0.113*	0.000
	(0.049)	(0.082)			(0.059)	(0.068)
Population change	-0.031**	-0.053*	0.003	0.084	0.038	-0.065*
	(0.012)	(0.031)	(0.036)	(0.055)	(0.030)	(0.035)
Lagged short-term interest	0.026***	0.028***	-0.013	-0.006	0.011**	0.005
	(0.005)	(0.007)	(0.008)	(0.010)	(0.004)	(0.005)
Lagged real GDP growth	-0.006***	-0.009***	0.010**	0.014***	-0.004**	-0.005**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)
Education	-0.028***	-0.032***	0.027	0.020	-0.029***	-0.036***
	(0.008)	(0.010)	(0.018)	(0.018)	(0.008)	(0.010)
High-tec sector	0.028	0.011	-0.015	-0.000	0.008	0.000
	(0.031)	(0.037)	(0.045)	(0.046)	(0.029)	(0.027)
2023	-0.057*	-0.051	-0.015	-0.128*	-0.107***	-0.075*
	(0.033)	(0.045)	(0.049)	(0.072)	(0.030)	(0.040)
2024	-0.104**	-0.080	-0.025	-0.101	-0.085*	-0.044
	(0.045)	(0.063)	(0.058)	(0.079)	(0.050)	(0.062)
Constant	3.978***	4.335***	-1.446	-1.192	4.767***	5.293***
	(0.660)	(0.782)	(1.279)	(1.361)	(0.688)	(0.801)
Observations	221	143	221	143	221	143
R-squared	0.462	0.498	0.180	0.226	0.489	0.543
Number of spatial units	74	48	74	48	74	48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the results for one of the robustness checks for the regressions models in Table 2. The model names in this table corresponds to the same model names in Table 2. As a robustness check, inflation is removed as a control variable to mitigate potential multicollinearity.

Table 12. Robustness check – replacing ln AI with lagged ln AI.

VARIABLES	(1.1) UNEMPLOY-MENT RATE (All)	(1.2) UNEMPLOY-MENT RATE (Regions)	(2.1) VACANCY RATE (All)	(2.2) VACANCY RATE (Regions)	(3.1) LABOR MARKET SLACK (All)	(3.2) LABOR MARKET SLACK (Regions)
Lagged ln AI	**-0.004**	**0.006**	**0.016**	**0.002**	**-0.004**	**-0.014**
	(0.062)	(0.055)	(0.051)	(0.064)	(0.059)	(0.062)
Lagged ln unemployment			-0.494*	-0.512		
			(0.266)	(0.352)		
Lagged ln vacancy rate	-0.175**	-0.158			-0.172**	-0.145
	(0.071)	(0.104)			(0.066)	(0.093)
Population change	-0.053**	-0.039**	0.030	-0.019	-0.033**	-0.035**
	(0.022)	(0.015)	(0.035)	(0.031)	(0.013)	(0.014)
Lagged short-term interest	0.007	0.016	0.002	-0.000	0.014**	0.018**
	(0.009)	(0.010)	(0.009)	(0.014)	(0.005)	(0.008)
Lagged real GDP growth	-0.009***	-0.019***	0.004	0.010**	-0.006**	-0.012**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.005)
Inflation	-0.014*	-0.001	-0.003	-0.003	0.002	0.021
	(0.007)	(0.015)	(0.009)	(0.019)	(0.006)	(0.013)
Education	-0.030*	-0.024	0.032*	0.022	-0.022*	-0.021
	(0.015)	(0.018)	(0.016)	(0.024)	(0.013)	(0.018)
High-tech sector	0.047	0.052	-0.058	-0.062	0.016	0.027
	(0.033)	(0.032)	(0.066)	(0.059)	(0.026)	(0.031)
2024	-0.110**	-0.105	-0.243***	-0.179*	-0.035	0.041
	(0.053)	(0.080)	(0.083)	(0.102)	(0.043)	(0.064)
Constant	4.133***	3.503**	-0.985	-0.401	4.087***	3.713***
	(1.182)	(1.375)	(1.235)	(1.848)	(0.996)	(1.366)
Observations	147	95	147	95	147	95
R-squared	0.451	0.519	0.397	0.439	0.341	0.359
Number of spatial units	74	48	74	48	74	48

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table presents the results for one of the robustness checks for the regressions models in Table 2. The model names in this table corresponds to the same model names in Table 2. As a robustness check, the independent variable ln AI is replaced with lagged ln AI in these regressions

Table 13. VIF results for Models 1-3.

Variable	(1.1)	(1.2)	(2.1)	(2.2)	(3.1)	(3.2)
ln AI	2.54	2.45	2.22	2.20	2.54	2.45
Lagged ln unemployment			2.33	3.86		
Lagged ln job vacancy	1.86	1.78			1.86	1.78
Lagged short-term interest	2.76	3.29	2.72	3.17	2.76	3.29
Education	1.97	2.02	2.77	4.67	1.97	2.02
Population change	1.84	2.00	1.85	2.11	1.84	2.00
Inflation	3.37	3.40	3.40	3.42	3.37	3.40
High-tech sector	1.67	1.55	1.66	1.60	1.67	1.55
Lagged real GDP growth	1.46	1.81	1.46	1.80	1.46	1.81
2023	3.20	3.62	3.16	3.61	3.20	3.62
2024	3.34	4.14	3.33	4.12	3.34	4.14
Mean VIF	2.40	2.61	2.49	3.06	2.40	2.61

The table displays the VIF results for the regressions in Table 2 to assess potential multicollinearity among the regressors. Since Stata does not allow to directly calculate VIF after fixed effects regressions, pooled OLS models with the same covariates and dummies are used.