Artificial Intelligence, Trade and Services Jobs

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Artificial Intelligence, Trade and Services Jobs

Hildegunn Kyvik Nordås* Aili Tang

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Abstract

This policy note studies the relationship between AI, services trade and jobs, piecing together micro evidence mainly from Sweden and sectoral evidence from WIOD and the OECD. There is a two-way relationship between AI and services trade. The use of AI makes services more tradeable through mode one, while services trade and cross-border data flows stimulate the development and affects the adoption of AI. Analysing Swedish vacancy notes during the period 2006-2020, we document that AI-related skills are still not widely sought after in labor markets, although demand has grown rapidly from a low base since about 2015, particularly in knowledge-intensive services sectors. Preliminary estimates using an extended version of the WIOD database suggest that AI exposure is associated with offshoring of AI-intensive services functions and that the marginal impact of offshoring on jobs depends on AI-exposure.

Keywords: Artificial intelligence; Services trade; Jobs

JEL Codes: F1, J24, L84

1 Introduction

Artificial intelligence (AI) could substantially reshape the content and skills requirements of existing jobs, create new occupations and eliminate others. Furthermore, while previous episodes of automation have mainly affected manual routine work, AI may automate some and enhance other functions performed by high-skilled white collar workers in knowledge-intensive business services (KIBS). At the same time, AI has the potential to substantially stimulate trade in services by making services more easily tradable across borders. This paper provides a descriptive analysis of the relationship between AI, jobs and trade in the KIBS, and link the description to insights from theory highlighting policy implications and areas for future research.

AI is ubiquitous, but business surveys consistently show that firms' uptake of AI is quite limited. For instance, comprehensive surveys from the US and Sweden find that less than 10% of all firms use AI.[1] Evidence from analyses of skills requirements in vacancy notes paint the same picture,

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[1]See Statistics Sweden and Zolas et al. 2021 for Sweden and ibid. for the US.

finding that less than 1% of all vacancy notes ask for AI skills. The share has risen sharply since 2015, but remains below 2% in most countries for which information is available.[2]

To understand the discrepancy between the omnipresence of AI and the subdued demand for AI skills as well as the meagre uptake of AI in firms, a distinction between the use and the development of AI is needed. While the development of AI requires sophisticated AI-skills, the use of AI may not. Thus, in a similar manner as computer software users do not need to know how to code, AI-skills may not be required to use AI-enabled services. Furthermore, if AI is running beneath an automated user interface, the user may not even be aware of the presence of AI. Finally, AI is associated with substantial economies of scale. A relatively small number of AI-developers can create services, including platforms, that reach global markets from a few locations around the world.[3]

International trade is driven by division of labor, either based on comparative advantage or a combination of love of variety and economies of scale. Consumers' love of variety combined with economies of scale leads to horizontal intra-industry trade, while gains from vertical fragmentation of production leads to vertical intra-industry trade and offshoring of services. The theory of trade driven by comparative advantage predicts that countries that are relatively abundant in AI-related skills and in which firms have access to huge amounts of data, would become major exporters of AI-intensive products. The theory of trade driven by product differentiation and economies of scale, on the other hand, predicts that lower trade costs leads to deepening division of labor and more intra-industry trade.

The role of AI in facilitating intra-industry trade is two-fold. First, AI-use reduces trade costs by enabling the digital transformation of products such that they can be transported over electronic networks including through cloud services. Second, AI enables the expansion of product variety. For instance, AI-driven algorithms help firms harvest customer data which can be used for mass customisation.[4] Furthermore, firms can also use AI to customise products to different regulatory requirements across jurisdictions, and thereby reduce policy-induced trade costs.

As we will see, KIBS are among the sectors with the highest demand for AI-related skills and also the most intensive users of AI. The main private sector AI developers are found in computer, internet and engineering services, while the other professions as well as finance are among the most intensive users of AI. We would therefore expect that large countries that are relatively abundant in AI related skills and in which firms have access to huge amounts of data are the main exporters of computer, internet and engineering services. The other KIBS are at the cusp of digital transformation and internationalisation in all countries, with rising intra-industry trade including offshoring.

The rest of the paper is organised as follows. The next section briefly reviews recent literature. Section three offers a comprehensive analysis of Swedish vacancy notes and the demand for AI skills by sector, firm characteristics and occupations. It also matches an index of occupational AI exposure to Swedish micro data on employment by occupation, industry, gender, age and level of education and analyses differences in AI exposure by worker characteristics. Section four presents preliminary empirical analysis of exports and offshoring of services functions, while section five concludes.

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[2] In the 2021 AI Index report from Stanford University, Singapore had the highest share of AI-vacancies at 2.5% (Zhang et al. 2021).

[3] Such enterprises have been described as having scale without mass in the literature (Brynjolfsson et al. 2008).

[4] See Tseng and Jiao 2001 for a study on mass customisation.

2 The literature

2.1 AI, skills and jobs

Empirical work on the relationship between AI, skills and jobs have been hampered by lack of reliable data. However, a small but growing literature has exploited online vacancy notes collected by Burning Glass Technology to study demand for AI-skills in the US (Acemoglu et al. 2020; Alekseeva et al. 2021; Blair and Deming 2020; Goldfarb, Taska, and Teodoridis 2021) and to a lesser extent the other 13 countries included in the Burning Glass database(Zhang et al. 2021; Squicciarini and Nachtigall 2021). These papers search for AI-skills in vacancy notes over an extensive period of time, calculate the share of total vacancy notes that contain AI-skills (i.e., AI-vacancies) and study the determinants of demand for AI-skills requirements as well as the impact of AI on wages.[5]

The papers differ somewhat in their definition of AI-vacancies. In Alekseeva et al. 2021 an AI-vacancy requires at least one AI-related skill from the list provided by Burning Glass Technology. In Squicciarini and Nachtigall 2021, however, an AI-vacancy contains at least two skills (or keywords in their terminology). It turns out that the share of AI-vacancies is highly sensitive to the definition. Exploring the robustness to different definitions, the latter paper finds that if the number of AI-skills is reduced to one, the AI-share increases 10-fold in the early period studied. Conversely, the share is halved when three keywords are used.

Analyses of the share of AI-vacancies by occupation and firm characteristics show that the AI-producing occupations i.e., computer and mathematical professions as well as engineering and architecture have the highest rate of demand for AI-skills. In addition to engineering and architecture, finance also ranks highly in AI-skills demand among sectors. However, while engineering plays a major role in developing AI, fintech firms are no less inclined to source AI from outside suppliers than other sectors according to the European Enterprise Survey on the use of Artificial Intelligence. Demand for AI-skills is observed across a broad range of AI-using sectors and occupations although less intensively than in AI-producing sectors. Demand for AI-related skills also varies across firm characteristics. Large and R&D intensive firms are much more likely to post AI-vacancies than smaller and less innovative firms (Alekseeva et al. 2021).

Growth and intensity in AI vacancies by country is reported in Zhang et al. 2021. The estimates are based on data from Linkedin profiles and suggest that AI may offer substantial opportunities for developing countries to make a technology leap. The highest AI-vacancy intensity is observed in Singapore with a ratio more than twice the US, which is a distant second. The fastest growth in AI vacancies are observed in Brazil, India and Canada. India also ranks at the top on the relative AI skill penetration rate, which measures the share of AI skills among the top 30 skills demanded in each occupation.

Finally, the literature has looked into which non-AI skills are requested in the AI-vacancies to assess possible complementarities between AI and non-AI skills. Soft skills including communication, problem solving, creativity and teamwork feature prominently among these, but also software and management skills go together with AI skills in vacancy notes. Furthermore, these non-AI skills have gained relative importance in AI-vacancies (Squicciarini and Nachtigall 2021; RPS Submitter et al. 2022).[6]

[5]See appendix table A1 for the list of AI-skills from Burning Glass Technology.

[6]Squicciarini and Nachtigall 2021 analysed vacancy notes from US, UK, Singapore and Canada.

To summarise, the literature so far suggests that AI has still not affected labor markets a lot, that demand for AI skills are growing fast from a low base and that AI skills are most sought after in large companies with AI development activities. The findings should be interpreted with caution, though since they largely build on Linkedin postings, which may not be equally representative in the countries covered.

2.2 AI and services trade

The link between AI and trade in services is multifaceted. Development of AI requires access to huge amounts of data. Therefore, large companies such as global platforms and companies using the internet of things (IoT) have a competitive advantage in developing AI-enabled services. Furthermore, if there are obstacles to cross-border data flows, large countries may have a comparative advantage for AI-driven innovation. Thus, the US has long been and still is at the AI technology frontier, but China is rapidly catching up and even surpassing the US on some AI metrics (Zhang et al. 2021).[7]

In Europe, AI-driven innovation faces challenges due to stricter regulation which curbs cross-border data flows as well as restricts the sharing of data with third parties (Li, Yu, and He 2019). That said, there is also the argument that European-style regulation is needed for people to willingly share their data. If EU-style regulation becomes widely adopted beyond the EU, as for instance its privacy standards have, firms complying with EU-style regulation may have a competitive edge. However, as noted by Geradin, Karanikioti, and Katsifis 2021 and Peukert et al. 2022, EU-style regulation may well benefit the large platforms. They have the resources to comply with the regulations while generating the data they need for e.g. training algorithms and customise products internally. Furthermore, regulation may not only allow them to restrict potential competitors' access to data, but even compel them to do so for privacy reasons. Either way, regulation on privacy and other rules on collection, storage and use of data has an impact on the development and competitiveness of AI-intensive services.

The digital transformation of services has made them more tradable across borders (Gervais and Jensen 2019).[8] However, even if the digital transformation started a couple of decades ago, cross-border trade (mode 1) has increased only modestly from about 26% of total services trade in 2005 to about 28% in 2017, the latest year for which data are available.[9] There are several reasons for this. First, services in general and knowledge-intensive services in particular are experience goods and rely on reputation for attracting customers. Reputation does not travel well. Second, regulatory heterogeneity combined with lack of clarity on processes and procedures for the recognition of qualifications and standards have clearly constituted a substantial obstacle to cross-border services trade in professional services and other regulated services (Nordås 2016).

While digitisation did not do much to boost cross-border services trade, AI might help overcome both the reputation and the regulatory obstacles to cross border trade. Thus, blockchain applications have reduced the importance of trust in any market, including services (Ali, Ally, Dwivedi, et al. 2020; Smits and Hulstijn 2020; Zavolokina, Zani, and Schwabe 2020), while AI-enabled software

[7]China has overtaken the US regarding the share of AI journal citations.

[8]International trade agreements such as the General Agreement on Trade in Services, consider all services tradeable, using an extended definition of trade, which comprises affiliate sales as well as people travelling abroad to provide or buy a service.

[9]Source: Trade In Services by Mode of Supply, TISMOS from the WTO.

that comply with local regulation at low costs for the user has entered many professions. Architects, for example, can work with clients anywhere using AI-enabled software and virtual reality to design a home or a commercial space. Furthermore, such software can be designed to incorporate the building codes of any country such that the architect can simply select the jurisdiction from a menu and ensure that the design is compliant with regulation. Such AI-driven functions can be an add-on service, or they can be an integrated part of the design software.[10] Another example is accounting where AI-enabled software embodying accounting standards and national tax codes reduces the compliance cost of offering services in many jurisdictions substantially.

Finally, there is also a link in the opposite direction from trade in services to the adoption of AI. First, the incentive to adopt AI-enabled automation software is stronger when labor costs are high. If services can be sourced from low-cost countries, for instance through remote teleworking, this would reduce the cost-advantage of automation and slow down the rate of adoption (Klügl, Kyvik Nordås, et al. 2021). Second, the data exhaust from digital services trade provides data for machine learning and the development of AI.

3 AI and skills: Insights from vacancy notes in Sweden

This section studies demand for AI skills inferred from Swedish vacancy notes using a similar methodology as Alekseeva et al. 2021. The analysis is based on the universe of vacancy notes posted on the Swedish Public Employment Services' website during the period 2006-2020. These include the majority of advertised vacancies in Sweden. We used the list of AI-related skills from Burning Glass Technologies (see appendix) and applied machine learning text analysis techniques to identify these skills in vacancy notes downloaded from the Pubic Employment Services.

3.1 AI skills intensity

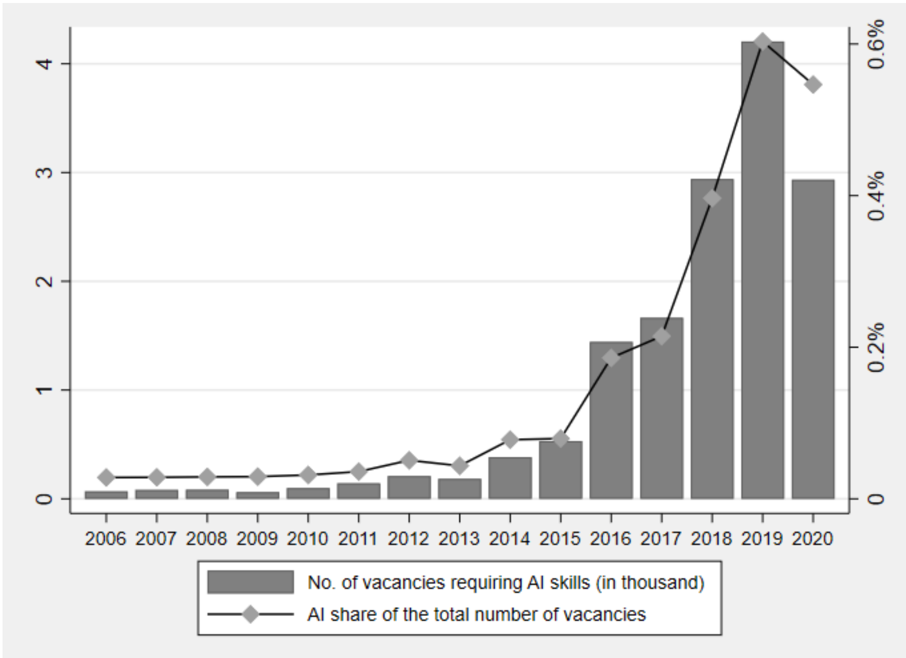
Swedish data confirms that demand for AI skills is small in absolute numbers but has seen a sharp rise from 2015 to 2019, followed by a drop in 2020 (Figure 1). According to the 2021 AI index report, a decline in 2020 was also observed for the US (Zhang et al. 2021). The decline is surprising since COVID-19 triggered a shift to online activities in all sectors and activities that possibly could, supported by rapid deployment of new technologies which rely on AI applications. However, the drop is consistent with the assumption that AI-use does not necessarily require AI-skills. Time will show whether this is simply a correction, a statistical artefact, or if demand for AI skills is already leveling off.

The AI skills most frequently demanded in job ads are reported in Table 1. The top ranking skill in the first three periods is machine translation (MT), which is overtaken by a wide margin by machine learning and also deep learning in 2020 (see also Figure 2). It is interesting to observe that the AI skills demanded correspond to tasks that AI *performs*. Thus, a reasonable interpretation is that the vacancies are mainly for AI developers.

The ten fastest growing AI-skills are depicted in Table 2. Automatic speech recognition (ASR) topped the list in the first period while sentiment analysis came first in the most recent period. In general it appears that the latest advances in AI-related skills take the top spot in each period.

[10] UpCode is an example of a firm that offers building code compliance tools for architects across the United States. See also Pena et al. 2021 for a fascinating discussion of the use of AI in architecture.

Figure 1: *The demand of AI skill in the labour market, 2006-2020*



Notes: The figure shows the number of vacancies requiring AI skills (bars) and the ratio of the number of vacancies requiring AI skills to the total number of vacancies (line). The calculation is based on the Swedish Public Employment data set.

Table 1: Top 10 most demanded AI-skills over years

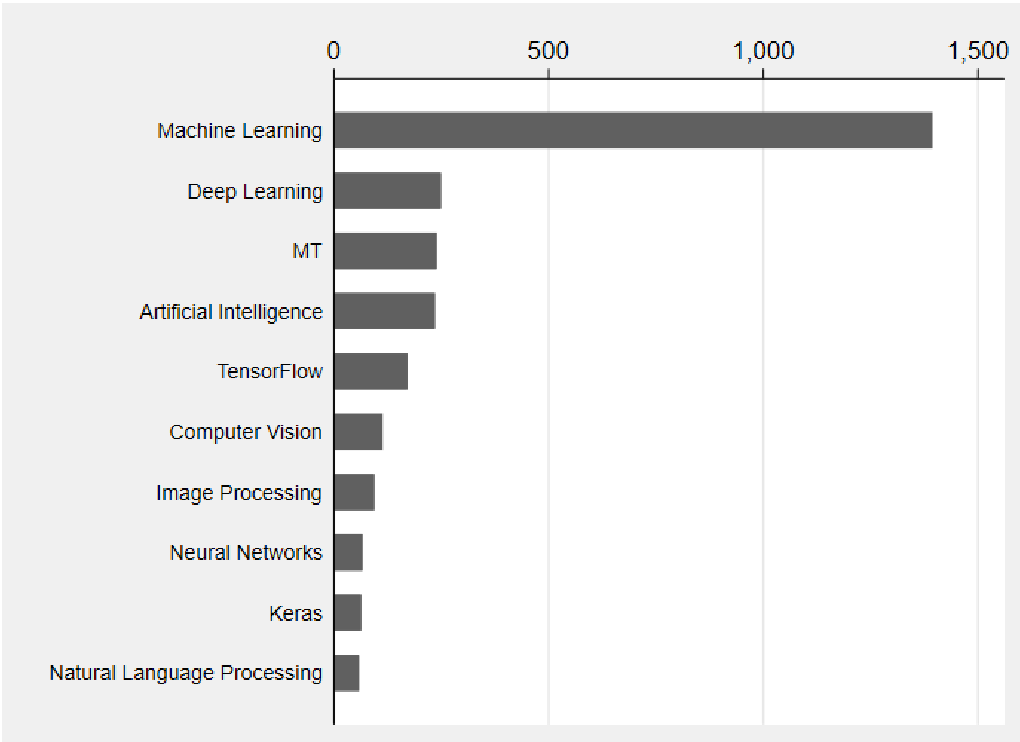
Year Rank	2008	2012	2016	2020
1	MT	MT	MT	Machine Learning
2	TTS	TTS	Machine Learning	Deep Learning
3	Image Processing	Machine Learning	Machine Vision	MT
4	ASR	Image Processing	Deep Learning	Artificial Intelligence
5	Speech Recognition	Machine Vision	ASR	TensorFlow
6	MoSes	Computer Vision	Image Processing	Computer Vision
7	Text Mining	Pattern Recognition	Artificial Intelligence	Image Processing
8	Artificial Intelligence	Natural Language Processing	Computer Vision	Neural Networks
9	Pattern Recognition	Artificial Intelligence	Natural Language Processing	Keras
10	SVM	OpenCV	Neural Networks	Natural Language Processing

Notes: The figure shows the top 10 AI skills sorted by the number of vacancies in which they are demanded in the Swedish Public Employment data set.

Demand for AI-skills have broadened substantially over the past decade as illustrated by Figure 3. The number of unique AI skills observed in the database of vacancy notes have almost quadrupled since 2010. This is in line with Squicciarini and Nachtigall 2021 who found a similar pattern for other countries. Furthermore, they found that not only has the number of AI skills and applications increased over time, but also the number of AI-related skills that a single worker must command.

Demand for AI-skills differ substantially across occupations and industries. Figure 4 shows devel-

Figure 2: *Most frequently required AI skills, 2020*



Notes: The figure shows the top 10 AI skills sorted by the number of vacancies in which they are demanded in the Swedish Public Employment data set in 2020.

opment over time for 1-digit occupation categories. AI skills are sought after in all occupations, but only in occupations requiring advanced level higher education was demand for AI skills reflected in more than 1% of vacancy notes in 2020. Occupations requiring higher education and managers are distant second and third in the ranking of occupations in which AI skills are in demand. We also observe that the demand for AI skills has risen sharply over time in the most AI-intensive occupations. The results for Sweden are similar to those found for the US, UK, Singapore and Canada (Squicciarini and Nachtigall 2021).

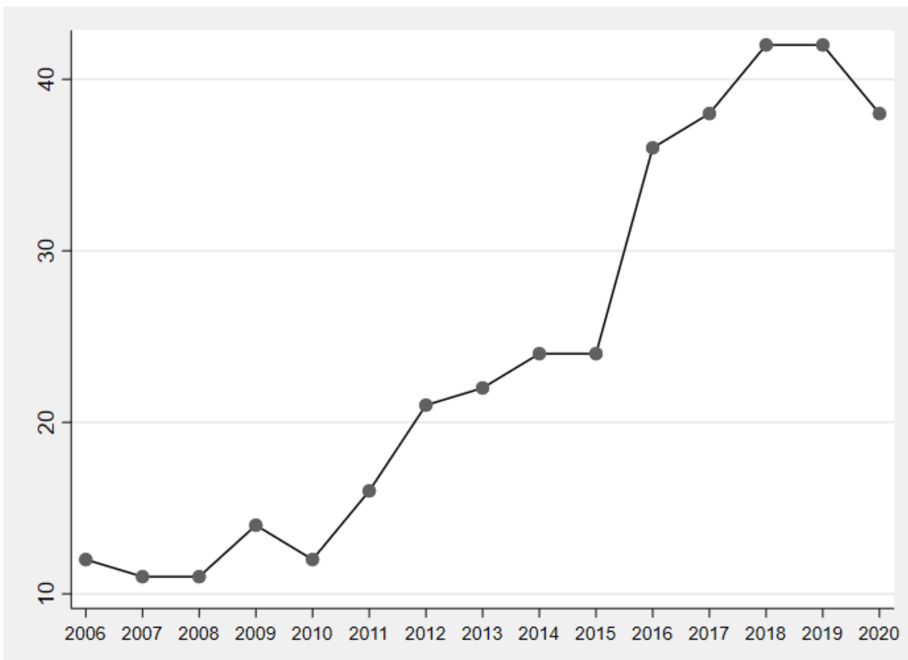
Turning to the distribution of AI-vacancies across sectors (Figure 5), wholesale and retail trade featured prominently in Swedish AI-demand in 2009 and 2010, accounting for almost 40% of all AI-vacancy notes. However, the share fell sharply in the next few years whereas knowledge-intensive business services (SNI-codes JKM) have dominated since 2015. Nevertheless, as indicated in the appendix figure A1, the AI-vacancy intensity is highest in the manufacturing sector. The share of AI-vacancies has risen sharply to reach about 1.5% in 2020 for the services included in codes JKM, still substantially behind manufacturing at 5% (See appendix Figure A1). This contrasts with the findings of Alekseeva et al. 2021 for the US economy, where information services and professional, scientific and technical services depicted about twice as high AI-vacancy intensity as manufacturing in 2019.

Table 2: Top 10 fastest-growing AI-skills demanded over years

Year / Rank	2008	2012	2016	2020
1	ASR	Pattern Recognition	Deep Learning	Sentiment Analysis
2	TTS	Machine Vision	Speech Recognition	Torch
3	Speech Recognition	Machine Learning	Computational Linguistics	Supervised Learning
4	MT	OpenCV	Object Tracking	NLTK
5	Machine Vision	Object Tracking	ASR	AI ChatBot
6	Image Processing	Computer Vision	IBM Watson	OpenCV
7	SVM	ASR	MT	Recommender Systems
8	MoSes	MoSes	Neural Networks	Machine Vision
9	Text Mining	MT	Machine Learning	Virtual Agents
10	Pattern Recognition	Opinion Mining	MoSes	TensorFlow

Notes: The figure shows the top 10 fastest-growing AI skills sorted by the number of vacancies in which they are demanded in the Swedish Public Employment data set.

Figure 3: *The number of AI skill demanded in the labour market, 2006-2020*

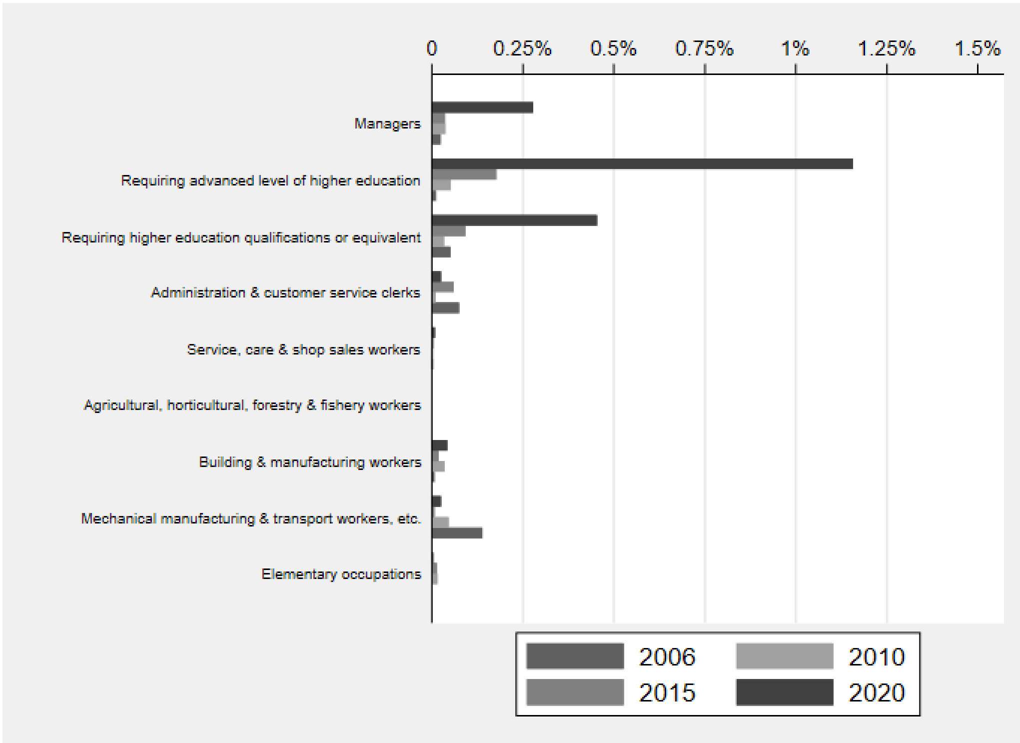


Notes: The figure shows the number of unique AI skills demanded in the Swedish Public Employment data set under2006-2020.

3.2 AI exposure

AI exposure is a measure constructed by matching the abilities required in occupations with the abilities of AI. It illustrates the potential for AI to automate the tasks and functions performed by the occupation (E. Felten, Raj, and Seamans 2021; Webb 2019). As indicated in the literature as well as by Appendix Figure A2, AI is most likely to affect high-skill jobs.

Figure 4: *AI-skill share by occupation over time*

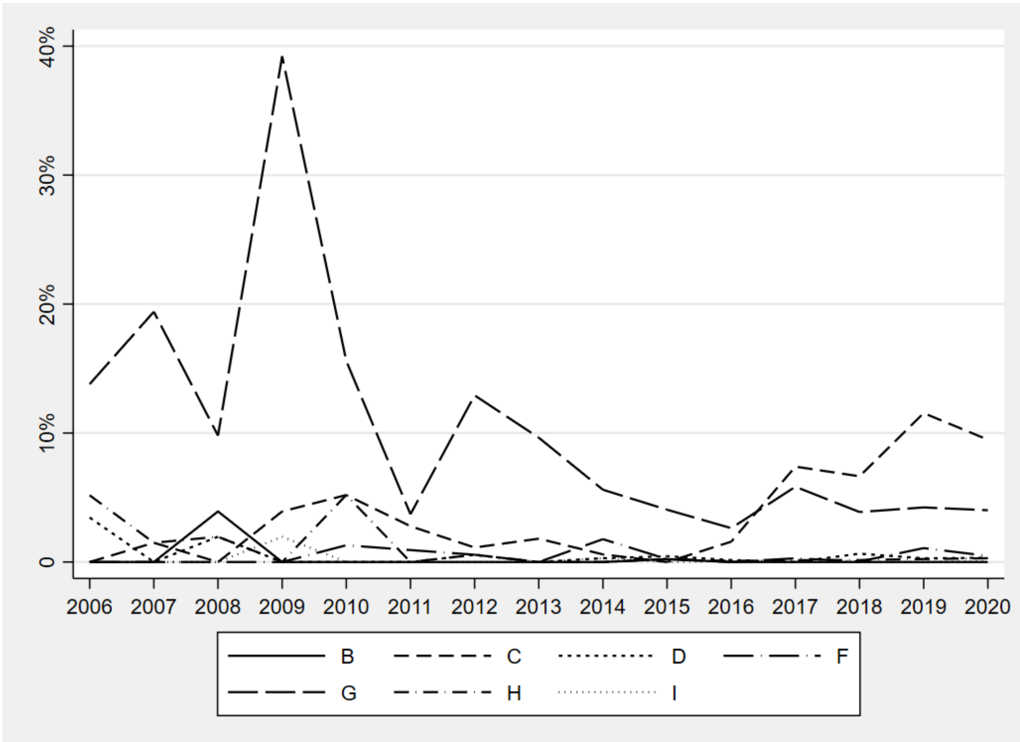


Notes: The figure shows the share of AI vacancies in the total number of vacancies by 1-digit occupations (first digits of SSYK 2012 code) under the year 2006, year 2010, year 2015 and year 2020. The sample is a full data set from the Swedish Public Employment. Data only includes job postings with non-missing SSYK 2012 codes.

We matched the AI exposure index developed by E. Felten, Raj, and Seamans 2021 to Swedish micro data on employment by occupation, gender and age to assess the AI exposure in the Swedish labour market. The results are reported in the charts below. We start with comparing workers the KIBS to the average of all occupations broken down by gender (Figure 6). As expected, KIBS workers are more exposed to AI than the average of all occupations. It is also noted that the AI-exposure were flat from 2001 to about 2013 when AI-vacancies started to rise rapidly as we have seen in the previous section. Finally, it is clear that men are more often employed in occupations that expose them to AI than women and the gender gap is larger for KIBS than for occupations on average. However, we also note that AI exposure has risen during the entire period for women in KIBS, and faster for women than men in recent years, although the gender gap in AI exposure is still wide.

A similar pattern appears when analysing AI-exposure by level of education. The exposure increases with the workers' level of education (Figure A2). AI exposure by age group reveals some unexpected results. First, for all sectors, the youngest workers are the least exposed to AI, suggesting that entry level jobs are not much exposed to AI. Nevertheless, AI-exposure started to rise earlier for the youngest workers in KIBS. For workers older than 25, age does not matter much for AI exposure,

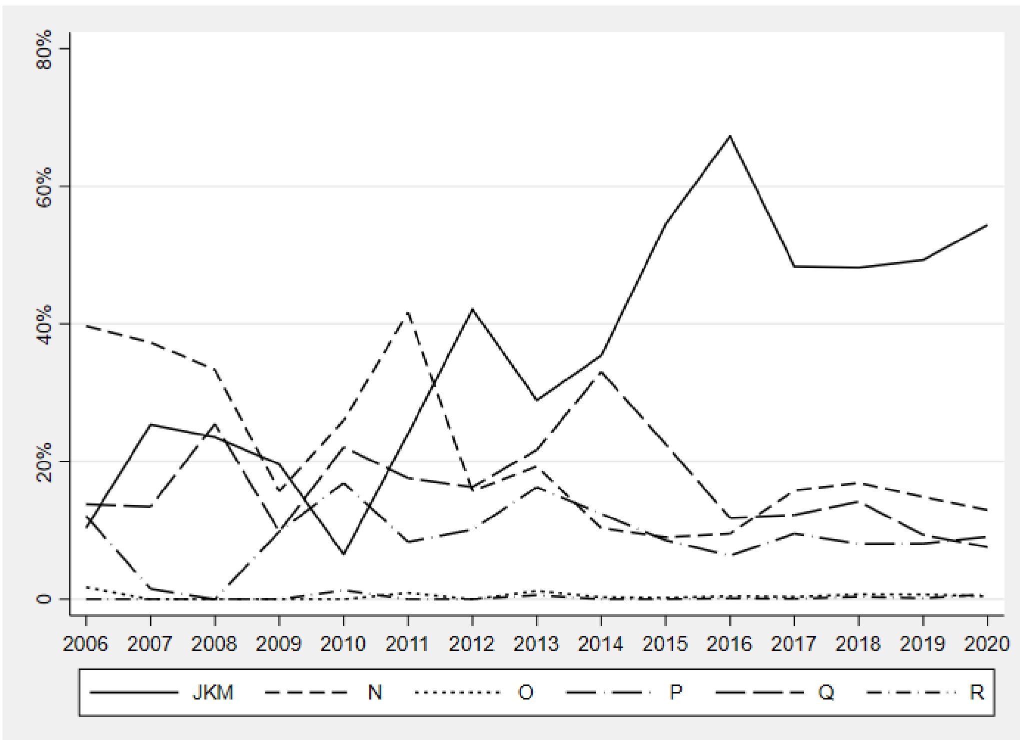
Figure 5: *(a) The distribution of AI vacancies by industry over time*



Notes: The figure shows the distribution of AI vacancies by SNI 2007 codes at the top level under the year 2006-2020. Sample is a full data set from the Swedish Public Employment. Data only includes job postings with non-missing SNI 2007 codes. The classification is based on the division of SNI 2007 codes at the top level. B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air conditioning supply. F: Construction. G: Wholesale and retail trade; repair of motor vehicles and motorcycles. H: Transportation and storage. I: Accommodation and food service activities. The figures only show lines for those sectors accounting for at least 1% of the AI-related jobs postings identified in the analysis.

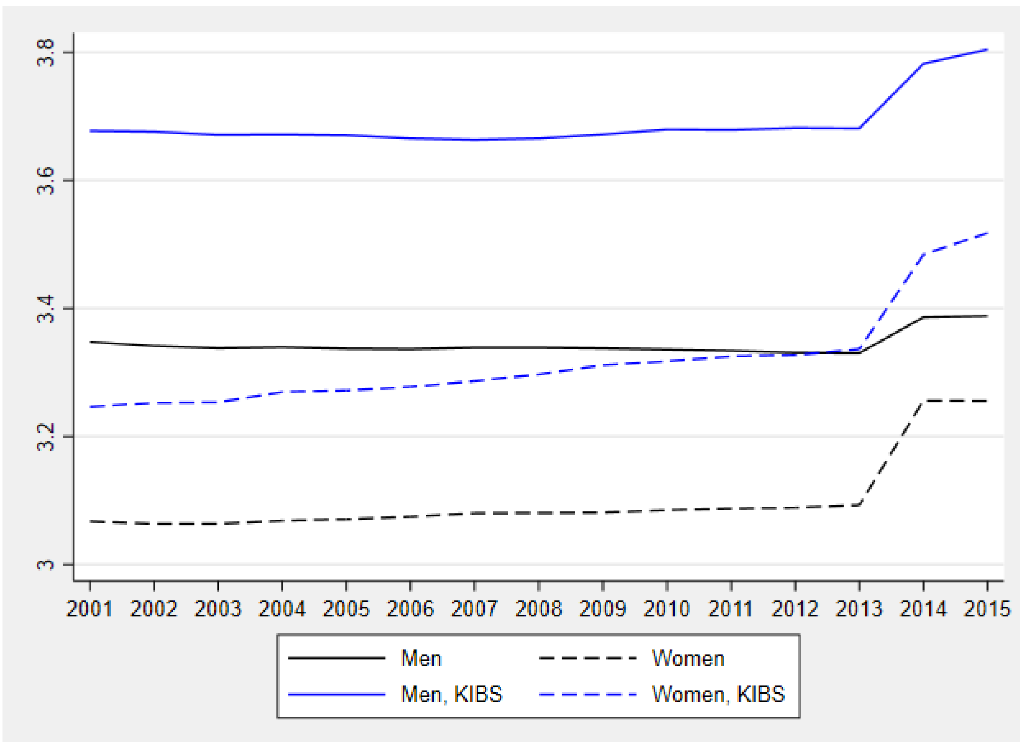
but to the extent that it does, AI exposure increases with age and is highest for the 65+ age group in KIBS. AI exposure does not necessarily mean that the worker currently holding a position use AI, only that the type of job he or she holds is exposed to AI. Thus, the disproportionate exposure of older workers to AI points to an urgent need for AI skills upgrading among older KIBS workers.

(b) The distribution of AI vacancies by industry over time



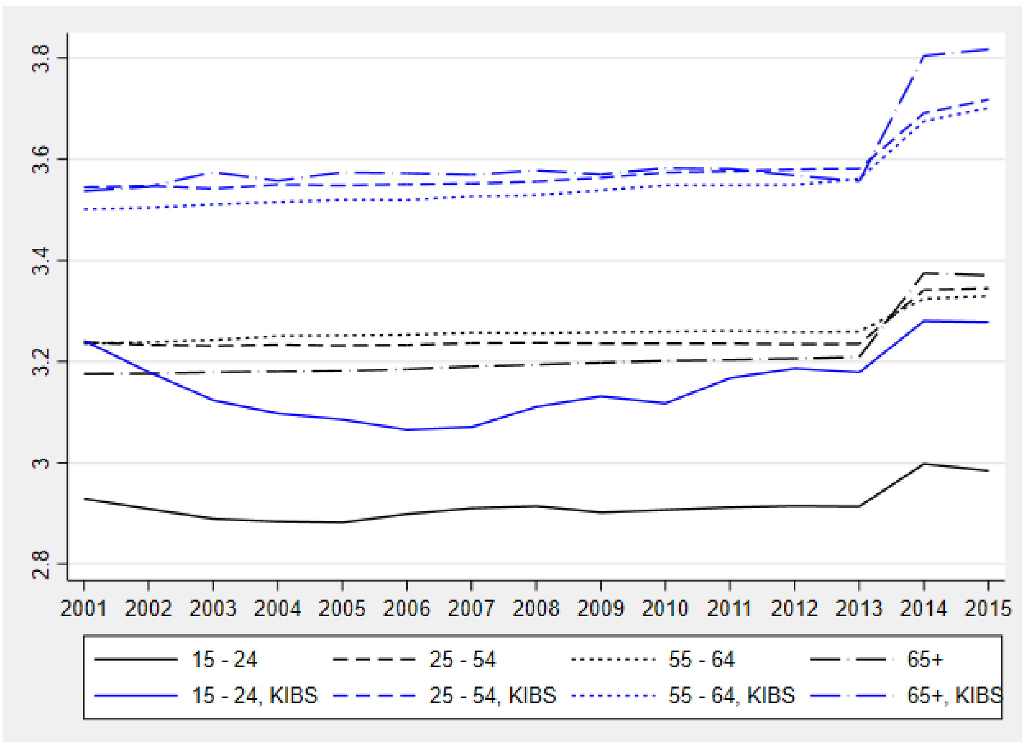
Notes: The figure shows the distribution of AI vacancies by SNI 2007 codes at the top level under the year 2006-2020. Sample is a full data set from the Swedish Public Employment. Data only includes job postings with non-missing SNI 2007 codes.The classification is based on the division of SNI 2007 codes at the top level. JKM: Information and communication; Financial and insurance activities; Professional, scientific and technical activities. N: Administrative and support service activities. O: Public administration and defence; compulsory social security. P: Education. Q: Human health and social work activities. R: Arts, entertainment and recreation. The figures only show lines for those sectors accounting for at least 1% of the AI-related jobs postings identified in the analysis.

Figure 6: *AI exposure by gender*



Notes: The figure shows the AI exposure by gender under the year 2001-2015.

Figure 7: *AI exposure by age group*



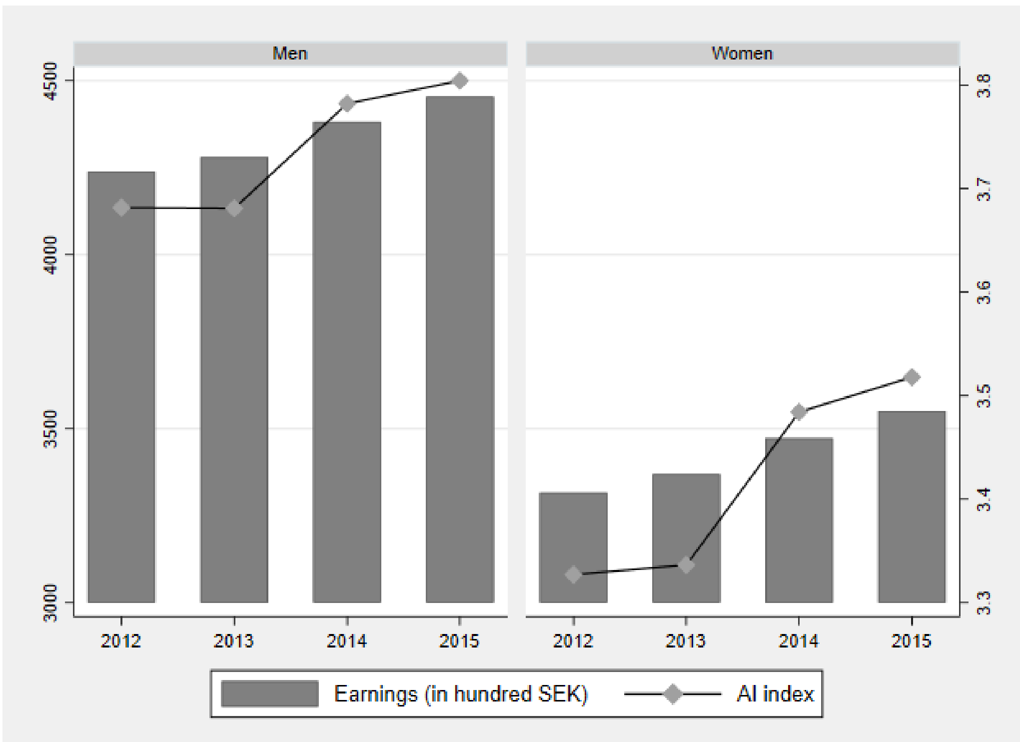
Notes: The figure shows the AI exposure (indicated at the vertical axis) by age group under the year 2001-2015. The AI exposure is based on occupation-level indicator from E. W. Felten, Raj, and Seamans 2019, which measures the exposure via the abilities of AI, and for performing an occupation. The KIBS industries are defined in Table A2.

3.3 AI and wages in KIBS

This section takes a closer look at the relationship between wages and AI exposure and a possible relationship between wages and trade. If AI-skills are scarce, rapid growth in demand for them could put upward pressure on wages in the occupations in which AI vacancies are most prominent. However, AI-skills abundance is also compatible with rising wages for workers with AI-skills, if Sweden specializes on AI-skills intensive sectors based on comparative advantage. On the other hand, if AI exposure is associated with automation of tasks, a downward pressure on wages in the occupations most exposed would be expected.

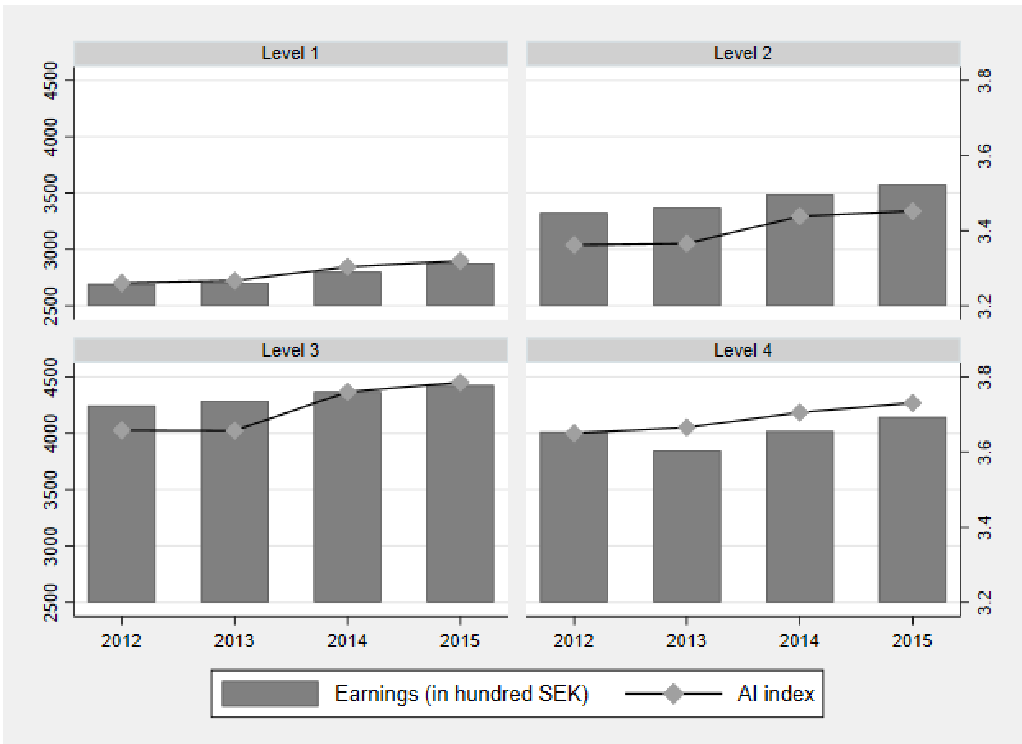
In the previous sections we have noted that KIBS industries are among the most AI-vacancy intensive sectors, while the KIBS occupations are the most exposed to AI. We also observe that KIBS occupations are found in all industries (see also appendix figure A3). Figures 8 to 11 plot annual average wages for different categories of workers employed in the KIBS industries against the AI exposure of the same category of workers. The overall take-away from these charts is that there does not seem to be a systematic relationship between AI exposure and wages. Both AI exposure and wages rise over time. AI exposure has increased slightly faster than wages, and marginally more so for women (Figure 8). Despite a higher level and increase in AI exposure among professionals, their wages have not grown slower than in other occupations (Figure 11). Conversely, while AI-exposure has declined in Services, Shop and Market Sale Workers, their wages have increased faster than in other occupations. Thus, at least up to 2015, there does not seem to be a systematic relationship between AI exposure and wages in the KIBS industries and we cannot infer a relation between trade and AI from this information.

Figure 8: *Differences in wage and AI exposure by gender in KIBS*



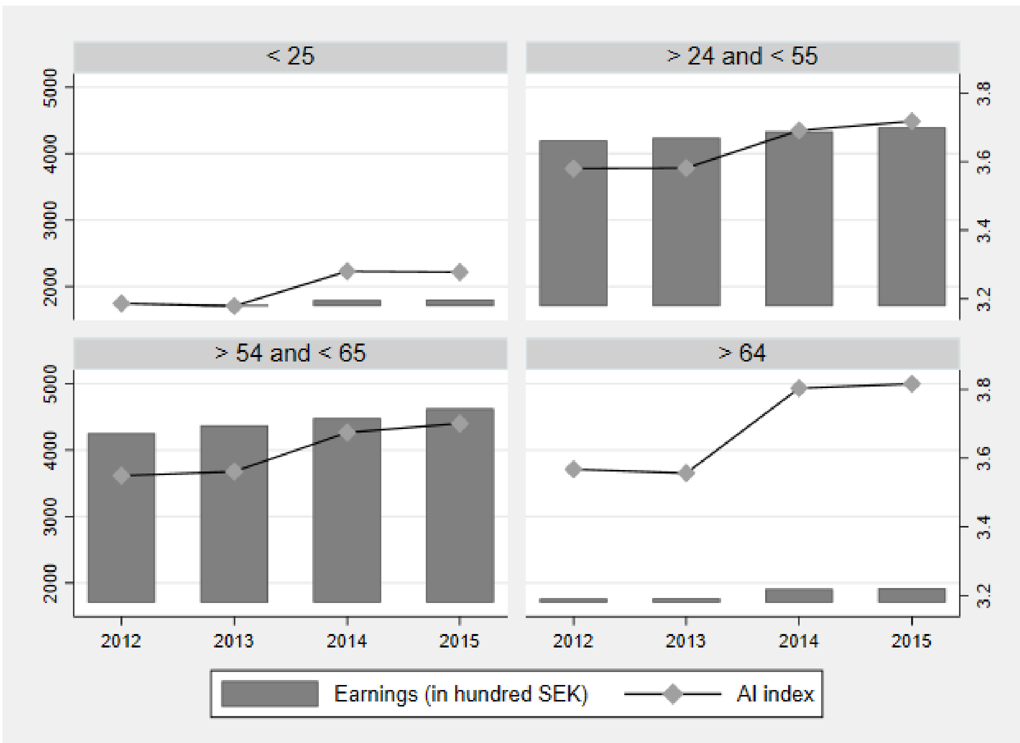
Notes: The figure shows the average annual full time equivalent wage in 100 SEK (indicated at the left side of the vertical axis) and AI exposure (indicated at the right side of the vertical axis) by gender under the year 2012-2015 in KIBS. The KIBS industries are defined in Table A2. The AI exposure is based on occupation-level indicator from E. Felten, Raj, and Seamans 2021, which measures the exposure via the abilities of AI, and for performing an occupation.

Figure 9: *Differences in wage and AI exposure by level of education in KIBS*



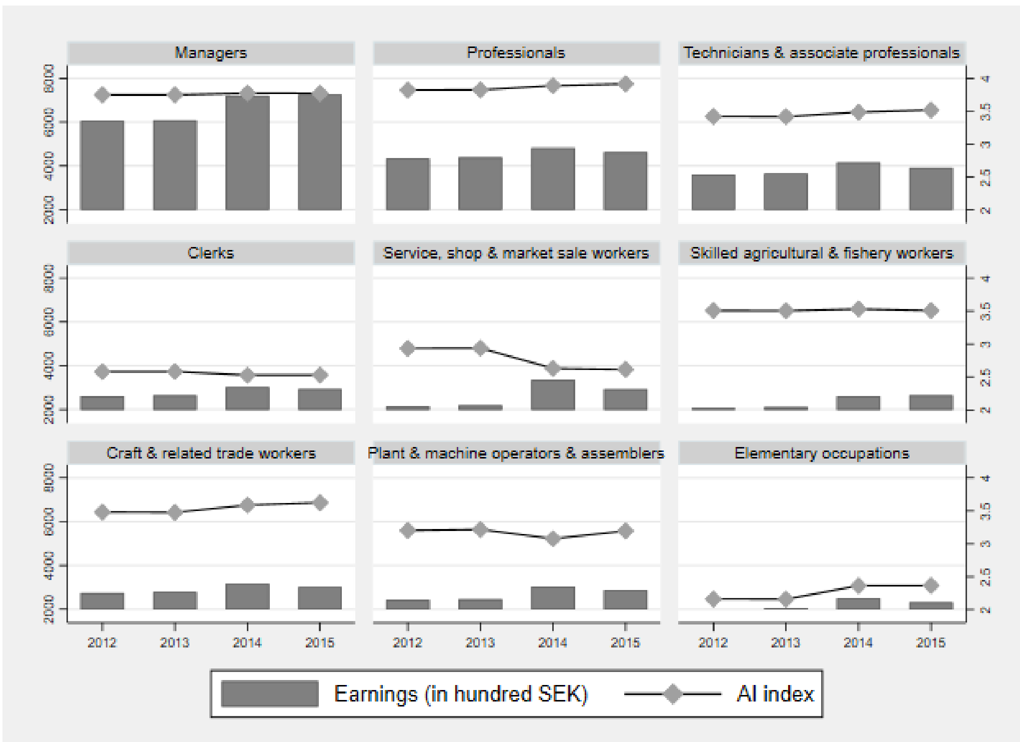
Notes: The figure shows the average wage (indicated at the left side of the vertical axis) and AI exposure (indicated at the right side of the vertical axis) by level of education under the year 2012-2015 in KIBS. The KIBS industries are defined in Table A2. The AI exposure is based on occupation-level indicator from E. W. Felten, Raj, and Seamans 2019, which measures the exposure via the abilities of AI, and for performing an occupation

Figure 10: *Differences in wage and AI exposure by age group in KIBS*



Notes: The figure shows the average wage (indicated at the left side of the vertical axis) and AI exposure (indicated at the right side of the vertical axis) by age group under the year 2012-2015 in KIBS. The KIBS industries are defined in Table A2. The AI exposure is based on occupation-level indicator from E. W. Felten, Raj, and Seamans 2019, which measures the exposure via the abilities of AI, and for performing an occupation. Notice that model estimation is used on filling in the data of wage for the age group 64+.

Figure 11: *Differences wage and AI exposure by occupation in KIBS*



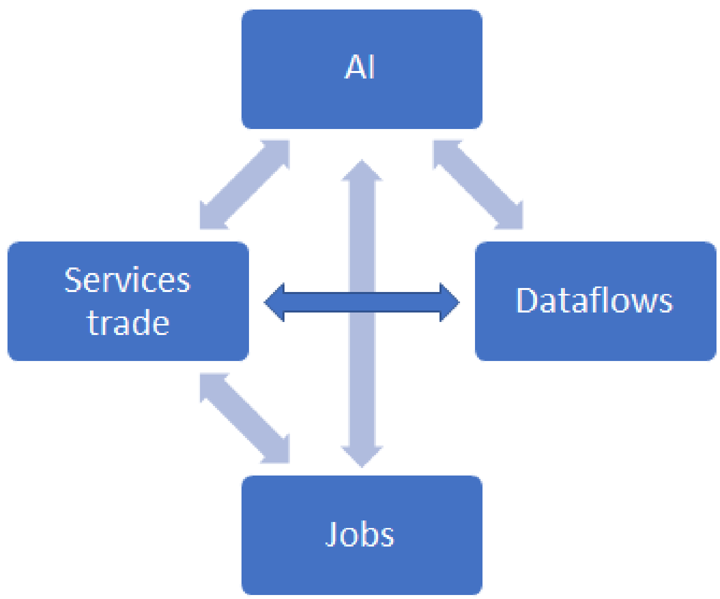
Notes: The figure shows the average wage (indicated at the left side of the vertical axis) and AI exposure (indicated at the right side of the vertical axis) by occupation under the year 2012-2015 in KIBS. The KIBS industries are defined in Table A2. The AI exposure is based on occupation-level indicator from E. W. Felten, Raj, and Seamans 2019, which measures the exposure via the abilities of AI, and for performing an occupation

4 AI, jobs and services trade

4.1 Qualitative analysis

Services trade affects both the uptake and impact of AI on KIBS jobs. First, digitization is typically a prerequisite for using AI applications (Bughin et al. 2017). Once digital, jobs can be performed remotely from anywhere with a decent communications infrastructure. The relationship between AI, services trade and jobs are illustrated in Figure 12. AI *use* has a direct effect on services trade by making services more tradeable, opening new opportunities for intra-industry trade and offshoring of services. Conversely, services trade affects the incentives to use AI for automating tasks and business functions. When the tasks and functions in question can be sourced more cheaply from low-cost countries, AI-driven automation may be delayed (Klügl, Kyvik Nordås, et al. 2021). AI also creates comparative advantage based on relative abundance of data and AI-skills shifting resources towards R&D, computer science and engineering services. Exports and FDI in these sectors strengthens competitiveness by exploiting substantial economies of scale.

Figure 12: *The relationship between AI, services trade and jobs*



Cross-border data flows affect AI both through services trade and directly. The direct channel involves data generated from customers and sensors around the world which feeds into training algorithms for developing AI applications. Cross-border data flows also support services trade such as a host of cloud services or streaming of audiovisual services, but also business process outsourcing that involves the transfer of data in any industry. AI enters the picture when firms source AI-enabled accounting, human resource management, supply chain management or preventive maintenance internationally.

AI affects jobs directly through automation, decision support and the augmenting of skills. As documented in the previous section, so far, AI appears to have had a limited direct impact on jobs. AI also affects jobs indirectly through services trade. As noted, countries that are relatively abundant in AI-related skills and have access to data have comparative advantage in AI-intensive services, i.e., the KIBS. Theory predicts that jobs will be reallocated to these expanding KIBS sectors from sectors facing new import competition. The data intensity of AI favors large countries including the US, China and the European Union, the latter if it could get its digital markets better integrated.

4.2 Empirical analysis based on WIOD and business functions

AI use reduces trade costs for services and should therefore stimulate services trade. For the KIBS, which are mainly intermediate inputs, AI use should stimulate outsourcing and offshoring. To explore this prediction empirically, we use the World Input Output Database (WIOD) extended by estimates of employment by business function from Miroudot and Cadestin 2017. They define seven business functions as listed below, where functions four, five and six are largely performed by workers in KIBS occupations.

- F1: Core business functions of the sector
- F2: Transport, logistics and distribution support functions
- F3: Marketing, sales, after sales services
- F4: IT services and software support
- F5: Management, administration and back-office support functions
- F6: R&D, engineering and related technical services
- F7: Other business functions, include maintenance, repair, security, education, and training

Nordås 2020 defines narrow outsourcing and offshoring of services as buying the services that perform these functions from local and foreign suppliers respectively. For instance, offshoring of IT services and software support (F4) is defined as intermediate imports of computer services.[11] She argues that this measure of narrow offshoring is the most relevant for analysing the relationship between offshoring and jobs. To bring AI into the analysis we add the E. Felten, Raj, and Seamans 2021 indicators of AI exposure (AIIE) by industry to the extended WIOD table.[12]

Since employment in the seven business functions in each sector is probably determined simultaneously, we run seemingly unrelated regressions (SUR) for offshoring of each of the seven business functions, controlling for wages, gross output and a dummy for manufacturing. The results are presented in Table 3.

We observe that a sector's AI exposure is significantly associated with offshoring of business functions. Sectors with a high AI-exposure tend to offshore less of their core business functions (F1) and transport and logistics (F2), while they tend to offshore more IT (F4), management (F5), R&D (F6) and other business functions (F7). The latter includes training, which is likely to drive the

[11] The extended WIOD database thus has information on employment by business function while the input-output structure is defined in terms of business functions.

[12] We used UN stats concordance tables for translating the AIIE indicators from NAICs to ISIC rev 4 and then aggregated them to WIOD sectors taking the simple average of the 4-digit categories entailed in each of the 2-digit sectors in WIOD.

Table 3: Offshoring of services functions and AI exposure

	lnF1	lnF2	lnF3	lnF4	lnF5	lnF6	lnF7
AIIE	-0.037***	-0.009***	-0.001	0.001***	0.011***	0.002***	0.002***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ln wage	0.046***	0.006***	-0.001*	0.000	0.002*	0.000	-0.002***
	(0.003)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
ln gross output	0.018***	-0.000	0.002***	-0.000***	0.007***	-0.000*	0.001***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
manuf.	0.317***	-0.014***	0.019***	-0.001***	-0.000	0.001*	0.002*
	(0.004)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
r2	0.416	0.074	0.182	0.245	0.190	0.112	0.185
N	15535						

Dependent variable is the log of imports of services corresponding to each business function. Regressions include country and year fixed effects. Since AI exposure (AIIE) is sector-specific and does not vary across countries and over time, sector fixed effects could not be included. Standard errors are reported in parentheses and ***, ** and * signify statistical significance at a 1, 5 and 10% level respectively

Table 4: Labor demand by services function

	lnL1	lnL2	lnL3	lnL4	lnL5	lnL6	l nL7
AIIE	-0.030***	-0.329***	0.104***	0.197***	0.182***	0.086***	-0.169***
	(0.007)	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)	(0.008)
manuf.	0.596***	-0.056**	0.142***	0.166***	-0.025*	0.417***	0.002
	(0.017)	(0.018)	(0.017)	(0.012)	(0.013)	(0.017)	(0.019)
ln outsourcing	0.399***	3.101***	0.446***	4.130***	1.064***	4.543***	1.654***
	(0.035)	(0.063)	(0.058)	(0.274)	(0.049)	(0.153)	(0.134)
ln offshoring	-0.516***	-1.626***	-0.007	-1.755*	-0.531***	-1.937***	-0.082
	(0.031)	(0.168)	(0.137)	(0.744)	(0.074)	(0.337)	(0.105)
r2	0.851	0.741	0.762	0.662	0.867	0.641	0.712
N	15464						

Dependent variable is the log of employment by business function. Regressions include country and year fixed effects. Since AI exposure (AIIE) is sector-specific and does not vary across countries and over time, sector fixed effects could not be included. Standard errors are reported in parentheses and ***, ** and * signify statistical significance at 1, 5 and 10% level respectively. The regressions control for wages, output, capital stock output prices and a manufacturing dummy. See appendix table A3

result for that function.[13] The business functions that are more often offshored from sectors with high AI exposure are functions performed by managers, professionals and technicians. These are also the occupations that are most exposed to AI in Sweden (figure 11).

The next step is to study the relationship between AI-exposure and employment by business function, controlling for wages, output, capital and outsourcing and offshoring. The results for the variable of interest are reported in Table 4, and the full regression results are reported in the appendix Table A3

Two results are worth noticing here. First, outsourcing of services functions to local suppliers are positively related to in-house employment in the same functions, suggesting that outsourcing and in-house employment complement each other. Offshoring, in contrast, is negatively associated with in-house employment. Second, the most AI-exposed sectors tend to employ more workers in the services functions that correspond to KIBS occupations (F4, F5 and F6), but also more workers in

[13]Other activities under other business functions are maintenance and cleaning, which are not easily offshorable.

marketing, sales and after-sales services (F3). Comparing the results to those reported in Table 3, it appears that AI-exposure is associated with both more offshoring and more employment in the KIBS related business functions.

To further explore the relationship between offshoring, AI exposure and employment by business function, we introduced an interaction term between offshoring and AI exposure. We first created a dummy that takes the value one if the AIIE index is higher than the mean and zero otherwise and interacted it with offshoring (Table 5)

Table 5: Labor demand by services function, AIIE interaction term

	lnL1	lnL2	lnL3	lnL4	lnL5	lnL6	lnL7
manuf.	-0.555***	0.490***	1.099***	1.292***	0.860***	1.480***	2.370***
	(0.055)	(0.061)	(0.061)	(0.054)	(0.051)	(0.066)	(0.067)
ln Outsourcing	0.004	-0.122*	-0.269***	1.447***	-0.108	0.591***	0.206
	(0.029)	(0.055)	(0.046)	(0.249)	(0.056)	(0.143)	(0.111)
ln Offshoring	-0.291***	-0.394***	0.906***	-0.022	0.418*	-2.876***	0.735**
	(0.032)	(0.091)	(0.135)	(1.560)	(0.207)	(0.793)	(0.279)
AIIE *lnOffshoring	0.452***	-0.223	-0.784***	-4.281**	-0.695***	0.772	-0.567
	(0.049)	(0.141)	(0.204)	(1.509)	(0.207)	(0.793)	(0.293)
r2	0.931	0.876	0.890	0.749	0.914	0.788	0.845
N	15464						

Dependent variable is the log of employment by business function. Regressions include country, year and sector fixed effects. Since AI exposure (AIIE) is sector-specific and does not vary across countries and over time, its direct impact is picked up by the sector fixed effects. Standard errors are reported in parentheses and ***, ** and * signify statistical significance at a 1, 5 and 10% level respectively. The regressions control for wages, output, capital stock output prices and a manufacturing dummy. See appendix table A4

The results indicate that the marginal effect of offshoring on labor demand depends on AI-exposure. Starting with the core function, a 10% increase in offshoring is associated with about 3% lower demand for workers for low AI-exposure sectors, but about 1.5% *higher* labour demand for high AI-exposure sectors. Management functions depict the opposite pattern where the marginal impact of offshoring is weakly positive for low AI-exposure sectors, but strongly negative for high-AI-exposure sectors. In marketing the marginal effect of offshoring on labor demand is positive, but much less so for high AI-exposure sectors. For IT functions, the result is also interesting. From Table 4, we see offshoring is negatively associated with employment in this function, while the result in Table 5 indicates that this only applies to high AI-exposure sectors, where the parameter is quite large (10% increase in offshoring is associated with 40% decline in employment in ICT functions). For the other functions, AI-exposure does not significantly affect the marginal impact of offshoring on labor demand.

5 Concluding remarks

Research on the relationship between artificial intelligence, jobs and services trade is still in its infancy. This paper has documented that demand for AI-related skills, extracted from vacancy notes, is still mute, but over the past five years or so, demand has grown rapidly. Knowledge intensive services and the occupations delivering such services have seen the fastest growth as well as the highest level of AI-intensity.

It has been widely anticipated that the digital transition in services would trigger a major shift in services trade from commercial presence to cross-border trade over electronic networks, i.e., from mode three to mode one. According to the WTO TISMOS database, the shift has been modest so far. Likely reasons for this are first, that services are experience products for which demand relies heavily on the services suppliers' reputation. Reputation does not travel well across borders, and suppliers therefore prefer to have a commercial presence to establish personal relations with customers. Second, many countries require professional services suppliers to have a local presence in order to market and sell their services.[14]

AI might alleviate some of the constraints on cross-border trade that digitisation did not. AI-enabled software can now be made to comply with local regulation at relatively low costs. In addition, AI creates user interfaces that allow suppliers and customers to co-create products remotely. Finally, using blockchain technologies for such interactions and collaboration dampens the importance of experience for trusting services suppliers. Indeed, our very preliminary regression results suggest that AI-exposed industries have a higher propensity to offshore AI-exposed business functions.

While AI has eased many of the remaining constraints on cross-border trade, regulation has not kept up. The professions are for instance subject to professional licensing that may be ill suited for a digitised global economy. The purpose of such regulation is to address the problem of asymmetric information when lack of information can harm consumers. However, AI clearly narrows the information gap between suppliers and consumers and with it the need for regulation.

The need for face to face interaction has shaped trade policy in the professions, which mainly relates to mutual recognition of qualifications and transparency in licensing procedures. In the past when cross-border trade was hardly an option that professionals would consider, the licensing system and restrictions on cross-border data flows may not have been a binding constraint on services trade. However, with the new opportunities for trade with trust that comes with AI and blockchains, the need for and the nature of regulation needs to be rethought.

As we have seen, cross-border data flows are essential for both the development and use of AI in the KIBS. Restrictions on such flows for privacy and national security reasons have been on the rise in recent years, and so have data localisation requirements for industrial policy purposes. While security and privacy are legitimate policy objectives, regulations on cross-border data flows need to be inter- operable such that access to data does not become a competitive advantage for the largest companies in the world. There is evidence that this is already happening. Furthermore, the possible contradiction between competition policy that obliges so-called gate-keeping platforms to share data on the one hand and privacy regulation on the other must be resolved.

More research is needed as better data on AI-use become available. There is a small, but growing body of research analysing the relationship between AI and jobs. Hitherto the main focus has been on manufacturing. As AI gains prominence in the services sectors enhancing the services provided, lowering the costs, in some cases to zero, and expanding the reach of services, more work needs to be done to understand the impact of existing and proposed regulation. It is particularly important to study the joint effect of privacy, national security and pro-competitive regulation in an international setting.

[14] The OECD STRI provides information on professions subject to such requirements.

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Appendix

Table A1: List of skills in the Burning Glass Technologies job vacancies data set used to identify AI vacancies

N	Skill	N	Skill
1	AI ChatBot	37	Mlpy
2	AI KIBIT	38	Modular Audio Recognition Framework (MARF)
3	ANTLR	39	MoSes
4	Apertium	40	MXNet
5	Artificial Intelligence	41	Natural Language Processing
6	Automatic Speech Recognition (ASR)	42	Natural Language Toolkit (NLTK)
7	Caffe Deep Learning Framework	43	ND4J (software)
8	Chatbot	44	Nearest Neighbor Algorithm
9	Computational Linguistics	45	Neural Networks
10	Computer Vision	46	Object Recognition
11	Decision Trees	47	Object Tracking
12	Deep Learning	48	OpenCV
13	Deeplearning4j	49	OpenNLP
14	Distinguo	50	Pattern Recognition
15	Google Cloud Machine Learning Platform	51	Pybrain
16	Gradient boosting	52	Random Forests
17	H2O (software)	53	Recommender Systems
18	IBM Watson	54	Semantic Driven Subtractive Clustering Method (SDSCM)
19	Image Processing	55	Semi-Supervised Learning
20	Image Recognition	56	Sentiment Analysis / Opinion Mining
21	IPSoft Amelia	57	Sentiment Classification
22	Ithink	58	Speech Recognition
23	Keras	59	Supervised Learning (Machine Learning)
24	Latent Dirichlet Allocation	60	Support Vector Machines (SVM)
25	Latent Semantic Analysis	61	TensorFlow
26	Lexalytics	62	Text Mining
27	Lexical Acquisition	63	Text to Speech (TTS)
28	Lexical Semantics	64	Tokenization
29	Libsvm	65	Torch (Machine Learning)
30	Machine Learning	66	Unsupervised Learning
31	Machine Translation (MT)	67	Virtual Agents
32	Machine Vision	68	Vowpal
33	Madlib	69	Wabbit
34	Mahout	70	Word2Vec
35	Microsoft Cognitive Toolkit	71	Xgboost
36	MLPACK (C++ library)		

Table A2: List of KIBS Industries

Industry	*Description*
62010	Computer programming activities
62020	Computer consultancy activities
62030	Computer facilities management activities
62090	Other information technology and computer service activities
63110	Data processing, hosting and related activities
63120	Web portals
63910	News agency activities
63990	Other information service activities n.e.c.
69101	Legal advisory and representation activities of solicitor's firms
69102	Other legal advisory activities
69103	Advisory activities concerning patents and copyrights
69201	Accounting and bookkeeping activities
69202	Auditing activities
69203	Tax consultancy
70210	Public relations and communication activities
70220	Business and other management consultancy activities
71110	Architectural activities
71121	Construction and civil engineering activities and related technical consultancy
71122	Industrial engineering activities and related technical consultancy
71123	Electric engineering activities and related technical consultancy
71124	Engineering activities and related technical consultancy in energy, environment, plumbing, heat and air-conditioning
71129	Other engineering activities and related technical consultancy
71200	Technical testing and analysis
72110	Research and experimental development on biotechnology
72190	Other research and experimental development on natural sciences and engineering
72200	Research and experimental development on social sciences and humanities
73111	Advertising agency activities
73112	Delivery of advertising material
73119	Other advertising activities
73120	Media representation
73200	Market research and public opinion polling

Notes: The table displays the industries that are identified as knowledge-intensive business services (KIBS) industries by Schnabl and Zenker (2013) at the 5-digit level of the Swedish Standard Industrial Classification (SNI 2007).

Table A3: Labor demand by services function

	lnL1	lnL2	lnL3	lnL4	lnL5	lnL6	lnL7
ln wage1	-1.431***	0.170***	0.290***	0.183***	-0.081***	-0.046*	-0.180***
	(0.021)	(0.023)	(0.023)	(0.016)	(0.016)	(0.022)	(0.024)
ln wage2	0.209***	-0.773***	0.025	0.069***	-0.025	0.104***	0.065**
	(0.021)	(0.022)	(0.023)	(0.016)	(0.016)	(0.022)	(0.023)
ln wage3	-0.119***	-0.071***	-1.047***	0.001	-0.130***	0.320***	-0.006
	(0.015)	(0.016)	(0.017)	(0.012)	(0.012)	(0.016)	(0.017)
ln wage4	0.080***	0.128***	0.148***	-0.306***	0.021	-0.106***	0.032
	(0.018)	(0.019)	(0.019)	(0.014)	(0.014)	(0.019)	(0.020)
ln wage5	-0.032	-0.059*	0.161***	-0.093***	-0.494***	-0.204***	-0.069*
	(0.024)	(0.026)	(0.027)	(0.019)	(0.019)	(0.026)	(0.028)
ln wage6	0.098***	0.062***	-0.005	-0.024	-0.018	-0.486***	0.069***
	(0.016)	(0.018)	(0.018)	(0.013)	(0.013)	(0.017)	(0.019)
ln wage7	-0.101***	-0.202***	-0.340***	-0.063***	-0.253***	-0.021	-0.823***
	(0.021)	(0.023)	(0.024)	(0.017)	(0.017)	(0.023)	(0.025)
ln Price intermediate	0.073 -	0.086	-0.051	-0.013	0.403***	0.288***	0.752***
	(0.076)	(0.082)	(0.084)	(0.059)	(0.060)	(0.081)	(0.087)
ln K	-0.217***	-0.087***	-0.084***	-0.033***	-0.161***	-0.107***	-0.186***
	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)	(0.009)
ln GO	1.064***	0.649***	0.711***	0.368***	0.872***	0.581***	0.849***
	(0.010)	(0.011)	(0.011)	(0.008)	(0.008)	(0.011)	(0.011)
ln Price GO	-0.176*	0.112	0.127	0.065	-0.432***	-0.346***	-0.735***
	(0.076)	(0.083)	(0.084)	(0.059)	(0.060)	(0.081)	(0.087)
ln Length	-1.624***	-1.401***	-2.359***	-0.976***	-2.290***	-1.441***	-2.202***
	(0.057)	(0.052)	(0.054)	(0.036)	(0.037)	(0.049)	(0.054)
AIIE	-0.030***	-0.329***	0.104***	0.197***	0.182***	0.086***	-0.169***
	(0.007)	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)	(0.008)
manuf.	0.596***	-0.056**	0.142***	0.166***	-0.025*	0.417***	0.002
	(0.017)	(0.018)	(0.017)	(0.012)	(0.013)	(0.017)	(0.019)
ln Outsourcing	0.399***	3.101***	0.446***	4.130***	1.064***	4.543***	1.654***
	(0.035)	(0.063)	(0.058)	(0.274)	(0.049)	(0.153)	(0.134)
ln Offshoring	-0.516***	-1.626***	-0.007	-1.755*	-0.531***	-1.937***	-0.082
	(0.031)	(0.168)	(0.137)	(0.744)	(0.074)	(0.337)	(0.105)
r2	0.851	0.741	0.762	0.662	0.867	0.641	0.712
N	15464						

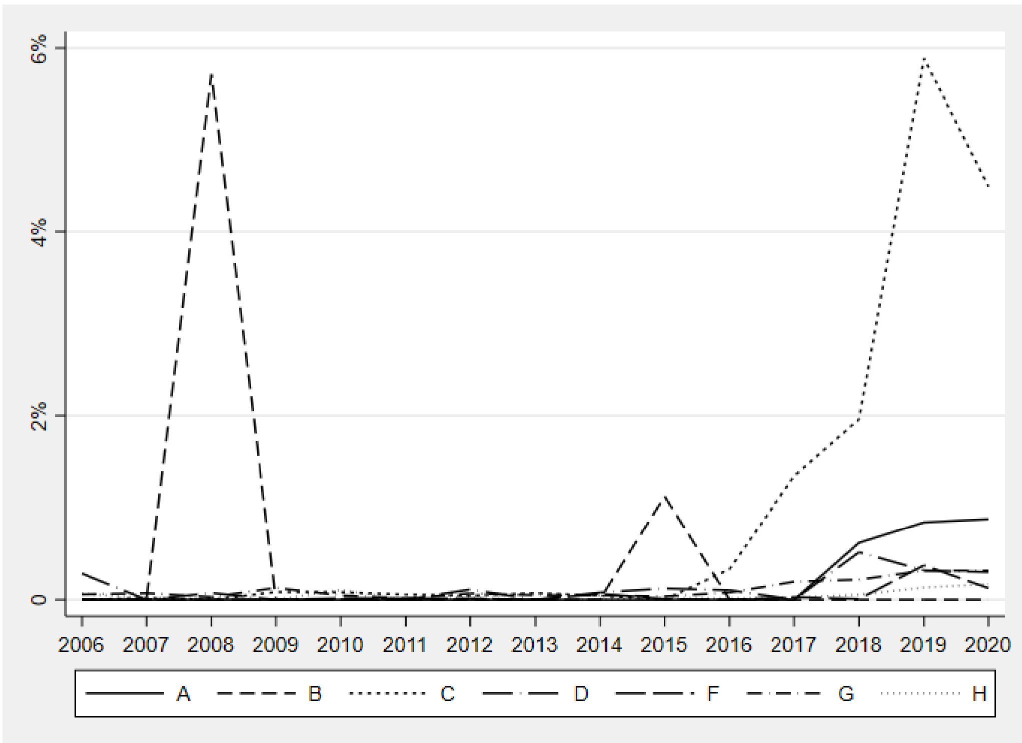
The seven wage variables refer to the average annual wage rate of each function in each country and year, price intermediate and price GO refer to a the price index of intermediate and gross output respectively as reported in the WIOD, K refers to the capital stock and length represents the length of the value chain (see Nordås 2020 for a discussion).

Table A4: Labor demand by services function

	lnL1	lnL2	lnL3	lnL4	lnL5	lnL6	lnL7
ln wage1	-0.802***	-0.148***	-0.026	-0.081***	-0.131***	-0.052**	-0.067**
	(0.017)	(0.018)	(0.019)	(0.016)	(0.016)	(0.020)	(0.021)
ln wage2	-0.009	-0.458***	0.152***	0.087***	-0.013	0.066***	-0.024
	(0.014)	(0.016)	(0.016)	(0.014)	(0.013)	(0.017)	(0.018)
ln wage3	-0.092***	0.063***	-0.420***	-0.027*	-0.017	-0.029*	-0.016
	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)	(0.014)	(0.014)
ln wage4	0.063***	0.111***	0.093***	-0.240***	0.014	-0.033*	0.048**
	(0.012)	(0.013)	(0.013)	(0.012)	(0.011)	(0.014)	(0.015)
ln wage5	0.004	0.006	-0.060**	-0.024	-0.394***	-0.040	0.025
	(0.017)	(0.019)	(0.019)	(0.017)	(0.016)	(0.021)	(0.021)
ln wage6	0.061***	0.033**	-0.015	0.001	-0.059***	-0.389***	0.079***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.010)	(0.013)	(0.014)
ln wage7	-0.074***	-0.175***	-0.207***	-0.089***	-0.088***	-0.002	-0.642***
	(0.015)	(0.017)	(0.017)	(0.015)	(0.014)	(0.018)	(0.019)
ln Price intermediate	-0.122*	-0.140*	-0.197***	-0.046	0.050	0.104	0.049
	(0.052)	(0.058)	(0.058)	(0.051)	(0.049)	(0.063)	(0.064)
ln K	-0.128***	-0.082***	-0.102***	-0.076***	-0.108***	-0.086***	-0.092***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
ln GO	0.850***	0.507***	0.530***	0.447***	0.705***	0.594***	0.623***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)
ln Price GO	0.016	0.162**	0.120*	-0.068	-0.125*	-0.092	0.025
	(0.053)	(0.058)	(0.058)	(0.052)	(0.049)	(0.063)	(0.065)
ln Length	-1.111***	-0.512***	-1.099***	-0.650***	-0.912***	-0.929***	-0.881***
	(0.049)	(0.048)	(0.048)	(0.042)	(0.041)	(0.051)	(0.053)
manuf.	-0.555***	0.490***	1.099***	1.292***	0.860***	1.480***	2.370***
	(0.055)	(0.061)	(0.061)	(0.054)	(0.051)	(0.066)	(0.067)
ln Outsourcing	0.004	-0.122*	-0.269***	1.447***	-0.108	0.591***	0.206
	(0.029)	(0.055)	(0.046)	(0.249)	(0.056)	(0.143)	(0.111)
ln Offshoring	-0.291***	-0.394***	0.906***	-0.022	0.418*	-2.876***	0.735**
	(0.032)	(0.091)	(0.135)	(1.560)	(0.207)	(0.793)	(0.279)
AIIE * ln Offshoring	0.452***	-0.223	-0.784***	-4.281**	-0.695***	0.772	-0.567
	(0.049)	(0.141)	(0.204)	(1.509)	(0.207)	(0.793)	(0.293)
r2	0.931	0.876	0.890	0.749	0.914	0.788	0.845
N	15464						

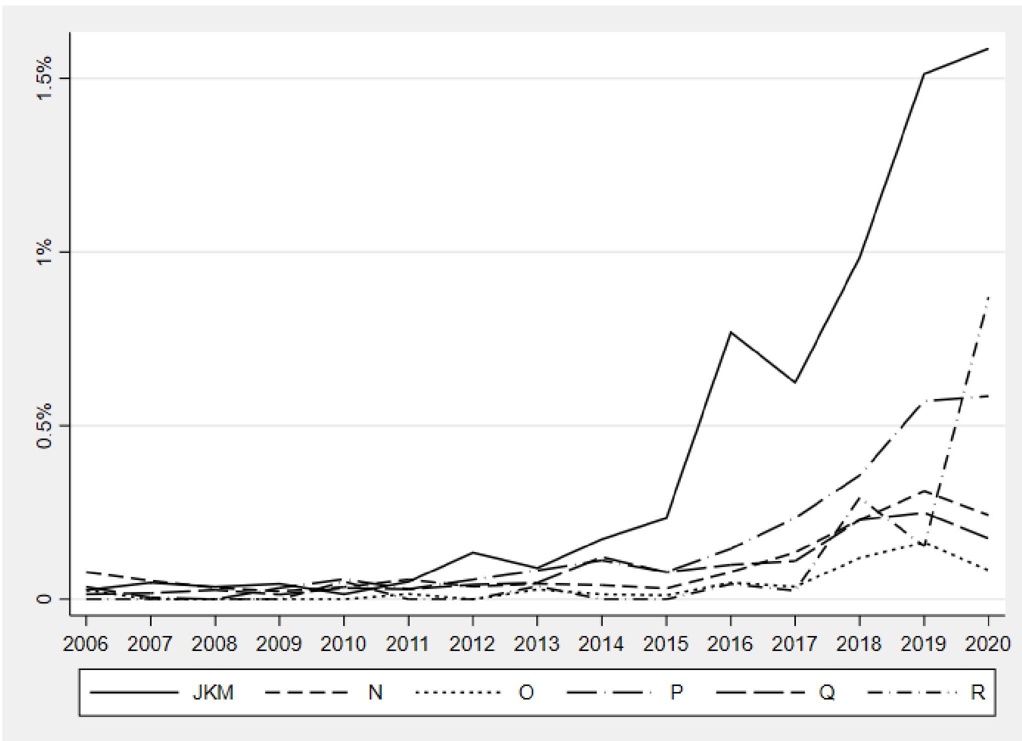
The seven wage variables refer to the average annual wage rate of each function in each country and year, price intermediate and price GO refer to a the price index of intermediate and gross output respectively as reported in the WIOD, K refers to the capital stock and length represents the length of the value chain (see Nordås 2020 for a discussion).

Figure A1: *(a) The share of AI vacancies by industry over time*



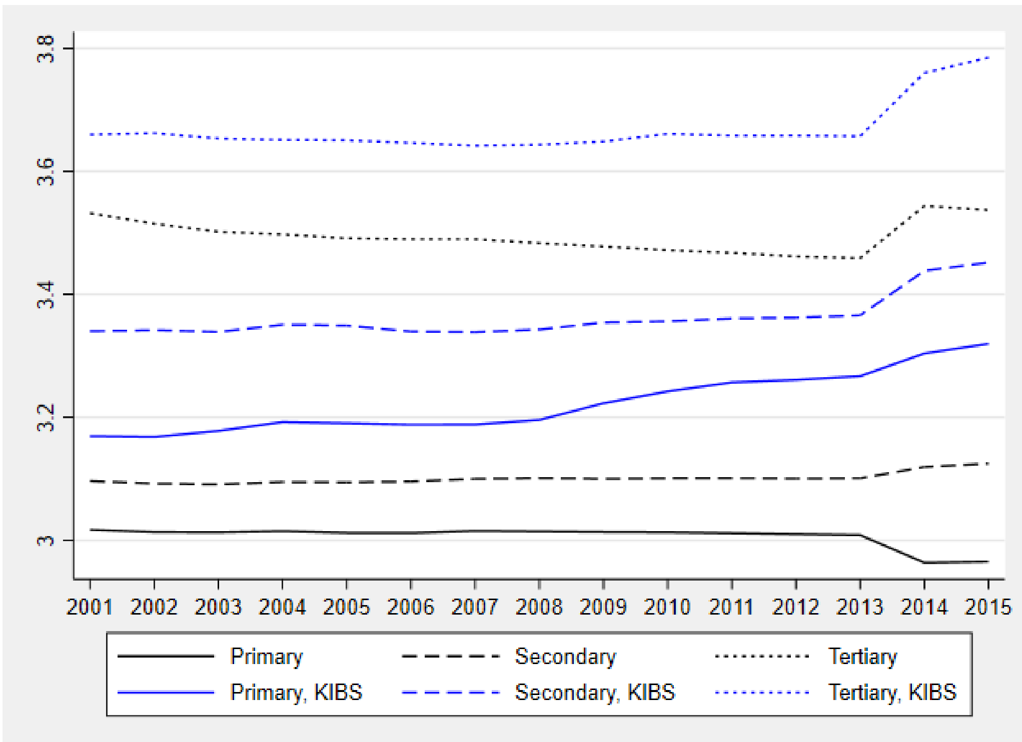
Notes: The figure shows the share of AI vacancies relative to all job postings by SNI 2007 codes at the top level under the year 2006-2020. Sample is a full data set from the Swedish Public Employment. Data only includes job postings with non-missing SNI 2007 codes.The classification is based on the division of SNI 2007 codes at the top level. A: Agriculture, forestry and fishing. B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air conditioning supply. F: Construction. G: Wholesale and retail trade; repair of motor vehicles and motorcycles. H: Transportation and storage. The figures only show lines for those sectors accounting for at least 0.1% of the AI-related jobs postings in relation to all job postings in the sectors identified in the analysis.

(b) The share of AI vacancies by industry over time



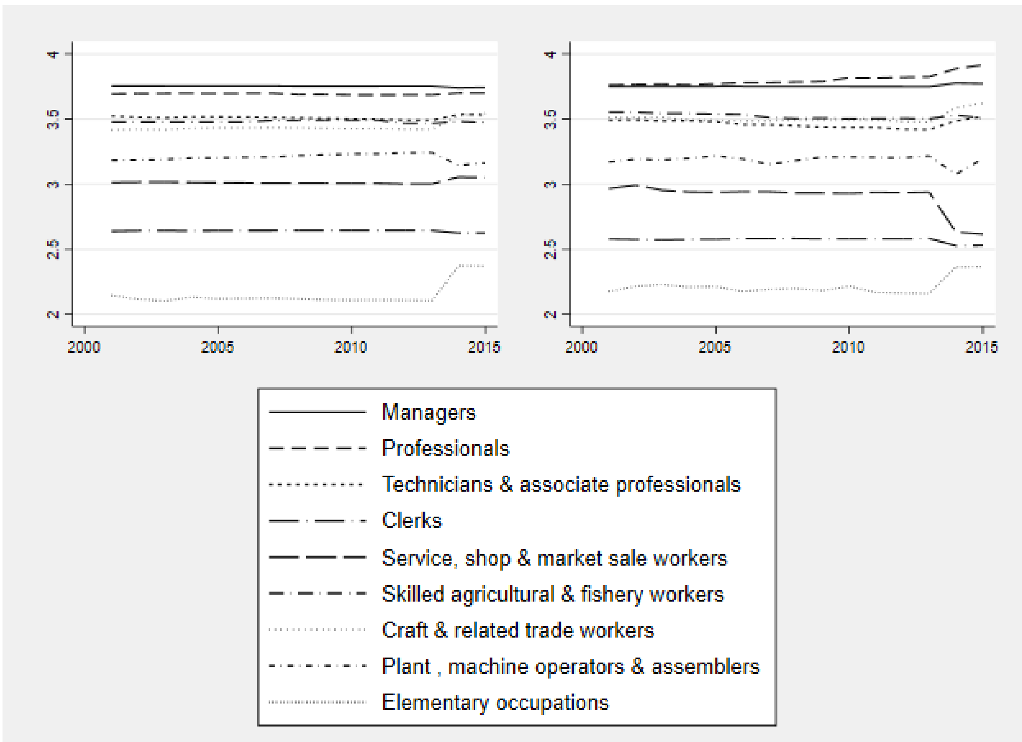
Notes: The figure shows the AI vacancies relative to all job postings by SNI 2007 codes at the top level under the year 2006-2020. Sample is a full data set from the Swedish Public Employment. Data only includes job postings with non-missing SNI 2007 codes.The classification is based on the division of SNI 2007 codes at the top level. JKM: Information and communication; Financial and insurance activities; Professional, scientific and technical activities. N: Administrative and support service activities. O: Public administration and defence; compulsory social security. P: Education. Q: Human health and social work activities. R: Arts, entertainment and recreation. The figures only show lines for those sectors accounting for at least 0.1% of the AI-related jobs postings in relation to all job postings in the sectors identified in the analysis.

Figure A2: *AI exposure by education level*



Notes: The figure shows the AI exposure (indicated at the vertical axis) by education level under the year 2001-2015. The AI exposure is based on occupation-level indicator from **fe2019***, which measures the exposure via the abilities of AI, and for performing an occupation. The KIBS industries are defined in Table A2.*

Figure A3: *AI exposure by occupation*



Notes: The figure shows the AI exposure (indicated at the vertical axis) by occupation under the year 2001-2015. The AI exposure is based on occupation-level indicator from **fe2019**, *which measures the exposure via the abilities of AI, and for performing an occupation. Left: not in KIBS. Right: KIBS. The KIBS industries are defined in Table*