Return of the Solow-paradox in AI? AI-adoption and firm productivity

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Abstract: AI-related technologies have become ubiquitous in many business contexts. However, to date empirical accounts of the productivity effects of AI-adoption by firms are scarce. Using Finnish data on job advertisements between 2013 and 2019, we identify job advertisements referring to AI-related skills. Matching this data to productivity data from ORBIS, we estimate the productivity effects of AI related activities in our sample. Our results indicate that AI-adoption increases productivity, with three important qualifications. Firstly, effects are only observable for large firms with more than 499 employees. Secondly, there is evidence that early adopters did not experience productivity increases. This may be interpreted as technological immaturity.Thirdly, we find evidence of delays of least three years between the adoption of AI and ensuing productivity effects (investment delay effect). We argue that our findings on the technological immaturity and the investment delay effect may help explain the so-called AI-related return of the Solow-paradox: I.e. that AI is everywhere except in the productivity statistics.

Keywords: Recruiting personnel, AI related jobs, Artificial Intelligence, Job Market, Text Mining, Firm performance, Productivity

JEL: D22, D24, O31, O32

1 Introduction

The use of digital technologies has revolutionized the ways of doing business for many firms and economic sectors (Brynjolfsson et al. 2018, Gal et al. 2019). Considerable evidence has accumulated that newer digital technologies, such as Big Data and software use in general, also affect firm

performance (Niebel et al. 2019, Branstetter 2019). Yet, in particular, for artificial intelligence (AI) as one the most advanced uses of ICT, the evidence is scarce (van Ark 2015), with most discussions remaining on a theoretical level (Acemoglu and Restrepo 2018, Gries and Naudé, 2018). That gap in the literature is conspicuous given that we have witnessed remarkable gains in the performance of the technologies in recent years. For example, Saon et al. 2017 show that error rates in voice recognition have plummeted as AI technologies improved. Gehring et al. (2017) showed how neural networks led to improved language translation, and Fortunato et al. (2017) reported on the successes of Google's DeepMind in Atari games. Despite these gains, anecdotal evidence suggests that the productivity effects related to AI may not appear automatically. Brynjolfsson et al. (2019) have termed this lack of evidence on conceivable productivity gains the "redux of the Solow (1987) paradox" arguing that "we see transformative technologies everywhere but in the productivity statistics".

While the lack of evidence of effects may indeed be the result of the lack of effects altogether, Brynjolfsson et al. (2019) argued that one of the reasons for the lack of evidence on effects on performance may be due to considerable time lags associated with AI. While time lags for the emergence of productivity effects are not uncommon for new technologies, they may be particularly relevant for AI because of two reasons. First, AI technologies may still be premature in the sense that they have not yet developed their full potential. One implication would be that early adopters may experience no or even adverse performance effects - an empirical regularity observable for many breakthrough technologies at the beginning of their life-cycle and summarized seminally in the concept of the technology-S-curve (Christensen 1992, Wonglimpyarat 2016, Priestley et al. 2020). A second mechanism that would imply an absence of productivity effects could relate to the lags between investment in AI and the emergence of any productivity-related returns. Brynjolfsson et al. (2019) argue that one reason for such investment delays is that AI is a transformative technology, which, besides learning to work with it, also requires systematic and holistic changes to the firm's overall structure. In particular, when the firm's organizational architecture is non-modular, such holistic changes may be costly and time-consuming (Agrawal et al. 2021).

Nevertheless, to date most of the claims about the presence or absence of the returns to AI have remained speculative, with concrete empirical evidence being scarce. In this paper, we focus specifically on the two arguments about why effects may be delayed (technological prematurity and investment delays) and how AI adoption rate affected productivity. We exploit unique Finnish panel data set on their job openings obtained from one of the leading commercial job advertisement Finnish job advertisement platform Oikotie Oy's. We match this data to economic performance measures, productivity in particular, which we collect from the ORBIS database. Overall, we obtain a panel dataset with performance measures obtained for the years 2016-2019 matched to AI-related job offers three years prior. Using fixed-effects panel regression, based on 721 firms, particularly large firms, we provide consistent evidence of a technological maturity effect, where early returns were negative in the beginning but turned positive at the end of the observation period. We also find evidence of significant investment delays meaning that returns occur only after significant time lags. The former is a technology-wide cohort effect, which would affect all adopting firms homogeneously at a particular time. Importantly, such a cohort effect would speak in favour of second mover advantages accruing to firms adopting AI only when the technology is ripe. Instead, the investment effect implies that all adopters have to go through an initial phase with no or negative returns. Only after this "investment" period, productivity gains can be achieved.

2 Literature review

2.1 Defining AI

Defining Artificial Intelligence (AI) is a subtle task and often causes confusion about the concept and how it relates to neighbouring concepts such as Big Data, Machine Learning or Deep Learning. In addition, there is no clear line of demarcation showing what should be still understood as an ordinary computation task or what is truly about "intelligence" in machines. Generally, what computers do is following certain rules and procedures (algorithms) to perform a task. AI is also based on algorithms but typically requires additional features to differentiate it from ordinary computation tasks. Generically, as Nilsson (2009) put it: AI is "that activity devoted to making machines intelligent". As of today, various implementations of AI exist, but their degree of "intelligence" differs. A hug subfield of AI is known under the term machine learning (ML) It means that a computer takes input - typically (large amounts of) data - to learn how to accomplish a certain task from it. ML is often but not necessarily about prediction or recognition in various fields: e.g. phenotypical species classification, stock price prediction, face recognition, predicting the creditworthiness of bank customers, or language recognition on a smartphone. The used algorithms are often remarkably successful in their tasks, even in very complex situations where deep human expert knowledge was regarded indispensable before. Tumour recognition and staging based on ML techniques is a point in case (Sharif et al. 2020). Despite these grand successes, many algorithms do arguably not derive their capabilities by infusing human "intelligence" into machines but by learning extremely effectively from (often huge) data sources (Friedman et al. 2001, James et al. 2013). As Agrawal et al. (2018) argued, the current wave of AI does not really bring intelligence but prediction as a key component of intelligence. A number of supervised learning algorithms such as linear regression, Support Vector Machines or Random Forests Classifiers as well as unsupervised learning algorithms such as cluster, principal component or factor analysis fall in this category of prediction and statistical learning algorithms. Even the often-cited artificial neural networks are, albeit powerful statistical learning, not intelligent.

AI-approaches that comer closer to behaviour, intuitively ascribe a certain level of intelligence to rely on the aforementioned statistical learning procedures but infuse goal-driven behaviour. Reinforcement learning (Sutton and Barto 2018) is a huge field in AI that employs an algorithm with preferences (which could be as simple as maximizing profits in a particular setting) and then allows the algorithm to change its behavior. Usually, these algorithms set out as quite dull instances but quickly improve their performance due to the available enormous computation power. Well-known examples are Google's AlphaGo, which taught Go to itself, and became so good at it that it finally beat Lee Sedol being one of the world's best professional Go players (Varian 2019).

While we do not intend to engage in a laborious attempt to define AI and demarcate it from ordinary computerized tasks, we can nonetheless infer to a few common observations and characteristics features. First, at the core of AI-related algorithms is the concept of statistical learning from often large amounts of input data. Second, the algorithms differ widely in terms of their degree of intelligence. Some ML techniques, which are arguably the most widespread, are pure statistical learners and are limited to narrow tasks, such as predicting creditworthiness. Other algorithms are substantially more complex and leverage data to modify and improve their own source code continuously. Thereby they become true learners in the sense that their original programmed state may not have much in common with their final state. Third, AI-implemented algorithms have proven to perform extremely well in a number of applications related to recognition and prediction that were thought to be reserved for human cognition before. Because of that, AI algorithms, irrespective of their degree of infused intelligence, had given rise to a myriad of value-creating business opportunities that, before the advent of AI, either were not possible to exploit at all or a least not at reasonable costs.

While the technological advances in AI suggest improving productivity at the firm level, the link between productivity and AI also depends on several techno-economic forces, including competition, heterogeneity between sectors, effects on minimum efficient scales of production, and the changing boundaries of the firm. In the next subsection, we will discuss the (limited) empirical literature on AI and will then continue with a theoretical discussion of how AI is likely to affect productivity on the firm level.

2.2 Empirical results on effects of AI and related technologies

Due to the novelty of IT-based technologies, empirical analyses are still scarce. Indeed, most studies have focused on the relatively older technology of industrial robots. Here, the primary interest was on the effects on employment and wages due to the potentially labour-saving effects resulting from automation. For example, Acemoglu and Restrepo (2017) find evidence that robots causally reduced both wages and employment in the US between 1990 to 2007. A comparable finding for Germany is presented by Dauth et al. (2017): The adverse effects may suggest that with increasing complexity, the technologies may turn to be substitutes rather than complements for labour. One paper by Graetz and Michaels (2015) focused on productivity and documented significant and positive effects on productivity growth. Together with negative effects on employment, the empirical results on the economic effects of industrial robots are indeed consistent with the hypothesis of labour-saving effects resulting from automation.

Additionally, several other studies also reported the positive impact on labour productivity for European manufacturers and developed countries in general but did not find a negative effect on employment (Fu et al. 2020, Dachs et al. 2022). Instead, rather indirect effects were suggested. e.g. Jäger et al. (2015) reported a negative effect on offshoring production outside Europe arguing that users of industrial robots are more frequently able to realize highly productive production processes in European high wage countries and, thus, help maintaining industrial production and value creation in the EU.

While it may be tempting to believe that AI has a similar labour-saving effect on high-skilled employment (Brynjolfsson and McAfee 2014), this is still unclear. Very recent survey results for AI seem to indicate that AI holds potentials for both job creation and destruction (Hunt et al. 2022). In particular, because AI and ML approaches are difficult to set up and calibrate appropriately, the increasing use of AI has certainly increased also the demand for data scientists and other IT-related high-skilled labour. In radiology, a profession sometimes argued to be on the verge of extinction, the number of employed experts has been on the rise rather than declining. Thus, AI, although for sure replacing certain job profiles, may create new ones through exhibiting powerful synergy effects. Indeed, Bessen (2017) argues that the effects of AI are likely to be heterogeneous across sectors. In particular, sectors with large shares of unmet demands (notably services), AI may prove to be more beneficial in terms of employment than in sectors where shares of unmet demands are lower (e.g. in manufacturing). Beyond such largely theoretical statements about the likely impacts of AI on employment, growth, profitability or productivity, empirical evidence of AI is mainly scarce. To date, one study Damioli et al. (2021) analyzes the effects of patenting AI-related technologies and find a productivity-enhancing effect. While these papers indicate the economic and innovative potential of AI, by focusing on patenting, they address primarily the commercialization value of the technology rather than the effects accruing to using or adopting AI-related technologies, which is at the core of this paper. The scarcity of the results of firm level effects of adopting AI on performance, is, as Raj and Seamans (2019) argue, largely due to an absence of specific firm level data on the adoption of AI in firms, which patent data on AI-related invention cannot easily approximate. Another reason is that even on the firm level, the effects are the result of technological advances and mediating and moderating economic forces. In the following, we intend to review important theoretical insights on the specific use of AI and how it is likely to translate into firm-level productivity. In the following, we will derive the concrete research hypotheses, where discuss first the baseline effect of the use and adoption of AI on firm-level productivity. Then, by drawing in insights from literatures on the dynamics of technology adoption (Christensen 2013) and investment and integration cycles (Agrawal et al. 2021), we will pay particular attention to the time profile of the effects.

2.3 The hypotheses

The previous section revealed that the direct evidence for the productivity effects of AI and related technologies is limited. However, the few existing works showed that there may indeed be positive productivity effects associated with both the use/adoption of IT-based technologies such as robotics (Graetz and Michaels 2015; Dachs et al. 2022) and the commercialization of AI-related technologies (Damioli et al. 2021). With limited empirical evidence, it is useful revisiting the theoretical aspects of AI technologies.

Conceptually, AI will increase productivity if it either decreases the required level of input for a given level of (monetarized) output or increases the output for a given level of input. While to date, we know little about whether AI is input-saving or value-increasing - if any of the two all - both mechanisms are theoretically conceivable. A number of examples exist, where AI progress has led to a tremendous decrease in costs for certain services and products. Varian (2019) cites the example of picture recognition, which is now offered by cloud-providers for less than a tenth of a cent per. Previously, reliable picture recognition would have relied on human cognition, implying higher costs by several orders of magnitudes.

The cost decreases can imply lower input requirements for already existing products and services on the market, as exemplified by picture recognition. Applications of picture recognition existed before the advent of AI, but were used only for very high-value activities. An example is clinical diagnostics based on MRI scans, which relied solely on human expert knowledge held by radiologists and now is in many cases aided or even replaced by machine learning techniques (Obermeyer et al. 2016). Applications now exist in a wide range of fields such as tumour detection (Zacharaki et al. 2009, 2011), Alzheimer diagnosis (Castellazzi et al. 2020), psychosis (Salvador et al. 2017) or Parkinson (Salvatore et al. 2014). Yet, the cost decreases in picture recognition associated with Machine Learning did not only contribute to making high-value tasks cheaper. It also helped e entirely new markets by making applications economically feasible, which would have been prohibitively expensive before. An example is Google lens, which is a consumer-focused web-service identifying practically all objects by comparing smartphone camera footage with existing pictures on the web. This application would have required a wide range of human experts two decades before and is not fully automated and free of charge for smartphone owners.

Besides reducing costs for the provision of existing goods and services or the creation of markets for new goods or services, several authors have highlighted the importance of AI-technologies for effectively implementing price differentiation. As Dubé and Mistra (2017) and Shiller (2013) show, it is possible to devise pricing models based onthird-order price differentiation, which can lead to a considerable transformation of consumer into producer rents through the use of information on the consumers' revealed preferences. Interestingly, such discriminatory pricing models are often considered sceptically from a welfare perspective because they transform consumers into producer rents. However, as Varian (2019) notes, price differentiation can create market segments at thelower-income range that would have been unserved under homogenous pricing. Therefore, the productivity effects originating from price differentiation may not only result from rent distribution but also from market and, thereby, rent creation.

In summary, we expect that AI has the potential to affect productivity positively through the reduction of costs for principally existing goods or services, through the creation of markets for entirely new goods or services and through the use of more effective use of price discrimination. We conclude with our baseline hypothesis H1:

H1: Higher use of AI increases firm-level productivity.

While H1 highlights the baseline expectation of positive productivity effects induced by the increasing diffusion and adoption of AI, a number of application-specific observations suggest that the actual state of technological progress may be lagging behind the occasionally excessive salvation promises. Langlotz (2019) argues that the promises of AI-based radiological diagnosis are still largely illusionary not only because of reluctant adoption but also because of slow technological progress resulting in particular from scarcity of training datasets and regulatory impediments. Chokshi et al. (2019) thus conclude that instead of replacing radiologists, experts in the field are more likely to learn to leverage AI technologies to improve their own diagnosis techniques over time. That observation that the technological benefits may unfold only in the long run also extend to other high-promise fields such as autonomous driving. While progress here is undeniable, with more and more aiding systems built into cars today, the technology is still far from offering ready-to-market autonomous driving solutions. A further reason is unresolved regulatory issues, particularly liability and privacy issues (Collingwood 2017). Thus, instead of disrupting entire technological and business fields from one moment to another, AI may transform them gradually over extended periods. Indeed, the concept of the technology S-curve proposed by Christensen (1992) made almost thirty years ago suggests that, fairly generally, technologies with a disruptive potential are unlikely to overturn existing technologies and business opportunities immediately. Instead the technologies may start with a performance level, which is inferior to existing incumbent solutions. The incumbent solutions, however are typically close to their maximum performance-level and therefore do not hold a promise of significant future improvements, while the disrupting technologies may hold this potential. One of the major conclusions for AI is that the productivity benefits associated with its adoption and use will accumulate with the increasing maturity of the technology over time. Therefore, several authors have highlighted that early second mover may experience advantages because they avoid adopting yet immature technologies (Asthana 1995, Jovanovic and Nyarko 1994). Early first adopters instead experience negative productivity effects by settling on a inferior technology, at least in the short run. At the same time, they still help seed the technology and thereby creating the basis for its future development (Catalini and Tucker 2016). The concept of the technology S-curve does not deny concept disruption but puts the assumption that disruption would be instantaneous as naive. Instead, associated gains on the firm level will grow with the increasing maturity of the technology over time. In line with this gradual accumulation argument, we conclude with our second hypothesis:

H2: The productivity effects of AI are larger in later cohorts.

H2 summarizes the expectation that the productivity effects of AI become only visible with a time lag that is dependent on the generic state of the technology and therefore common to all potential adopters. A second reason for time lags in the productivity effects is related to firm-specific integration and learning costs associated with the technology. Quite generally, new technologies put substantial pressure on adopting firms implying that gains are unlikely to be immediate. Most notably, the concept of learning-by-doing suggests that firms become acquainted with the technology and effectively use it only over time (Chuang 1998, Parente 1994, Bessen 2015). Consequently, the productivity effects of technology should, on the firm level, be a function of a time since adoption. Since these adoption times differ between firms, firm-level heterogeneity between firms plays a crucial role (Bessen 2017). While the literature on learning-by-doing effects associated with AI is still very limited, at least one study by Agrawal et al. (2021) exists that documents the substantial time lag on the firm level, which exists between adoption into AI adoption and any economic performance gains. The time lag results from substantial integration costs, which can prevent effective system-wide change and are increasing in the degree of non-modularity. Thus, even learning of the firm about AI will be associated with time lags. However, it is important to note that the time lags hypothesized in H2 should imply return patterns that differ over time but are similar across a firm. So to say, maturity effects in H2 are homogenous cohort effects. The time lags hypothesized summarized in H3 are a function of firm-specific adoption times and are therefore heterogeneous across firms.

H3: The productivity effects of AI increase in the time since adoption.

3 Data & methods

3.1 Data sources

In recent years, the availability of Big Data methods has greatly increased. While these types of data are typically unstructured and need cleaning before use (Gang-Hoon, Silvana, and Ji-Hyong 2014), they also offer analytic potentials that go beyond previously available structured data sources. One particularly relevant field is data on advertisements for text mining jobs have garnered interest from various scholars (e.g. Karakatsanis et al., 2017; Ningrum et al., 2020; Pejic-Bach et al., 2020), which holds the promise of providing valuable information on diverse topics, such as discrimination, skills and human capital characteristics (Kuhn, Shen, and Zhang 2020; Ningrum, Pansombut, and Pejic-Bach et al., 2020).

The ability to provide timely information on skill demands by firms is also the angle, which makes the data useful in our setting of measuring AI-adoption in firms. While so far AI has primarily been measured using either survey or patent data, these data sources each share certain disadvantages. Data collection via surveys is complicated, costly and only yields sometimes heavily biased sample data. Patent classifications can be useful but only refer to patentable inventions and therefore measure only firm activities that include the act of invention. Moreover, there are often long lags until novel technologies, such as AI, are robustly identified within patent classes. Job data offer timely access to information on AI-related activities inside firms that extends well beyond own inventive activities and may include even pure adoption of often existing technologies. In this paper, we make use of Oikotie Oy's data on job advertisements, which is one of the largest job advertisement databases in Finland.

The job ads dataset extends from 2013 to 2019 and contains 407,000 job advertisements. This period and particularly it's second half was a period of growth in the number of job vacancies. The largest number of job advertisements in the dataset, slightly over 90,000, was in 2019. The most significant growth in the yearly number of jobs, over 20,000 jobs, occurred in 2017. The growth also continued in 2018. For GDP, 2017 was also the period of rapid growth during the period considered; since then, annual growth has been lower.

The dataset includes full details of the job advertisement created by the job poster, such as job titles, job descriptions and information of which company had posted the ad. The most significant challenge with the data is using recruitment agencies without identifying the actual recruiting company.

We developed a three-tier glossary of terms and concepts describing AI to identify job ads aiming for AI-related skills. The glossary was built using publications where AI terminology and taxonomy were explained (Aristodemou et al. 2018; Brunette et al. 2009). Additionally, terms were picked from Stack Overflow survey results 2020[1], and from Wikipedia AI glossary[2]. Because the terms were of different levels of abstraction and specificity, the vocabulary was defined consisting of three tiers:

- Tier 1: Main general terms referring to AI (i.e., artificial intelligence, machine learning).
- Tier 2: Core technologies associated to AI (i.e., NLTK, Decision tree)
- Tier 3: Technologies that support or enhance AI solutions but not direct AI core technologies (i.e., Cloud, Database, Matlab)

The terms were defined in two languages (Finnish and English); many acronyms and product names were used as such in both languages and needed no translation.

The terms were searched in job titles and descriptions. Each job advertisement was linked to only one tier by starting from Tier 1, even though it might have had terms from Tiers 2 or 3. As a quality check, we assessed the job titles of the resulting dataset to check their relevance, and some ads were removed

1 Annual survey from software developers conducted by Stack overflow community: https://insights.stackoverflow.com/survey/2020

2 https://en.wikipedia.org/wiki/Glossary_of_artificial_intelligence

based on this before the analysis. The illustration of data processing steps is also available in Figure 5 in the annex.

The data on AI-related job advertisements was matched with basic economic and financial information from ORBIS. Although ORBIS offers principally more variables, we focused on operational turnover as well as the number of employees because acceptable coverage, thereby also providing an approximate measure of the company's productivity. The data set of AI job ads contained 3094 firms. Out of these firms, 821 companies could be matched to ORBIS. In the regressions, further item-non-response was a consequence of the data matching was mainly prompted by the non-availability of any information on financials in the ORBIS data. This extract is used for basic structural descriptions of firms offering AI jobs between 2013 and 2019.

Among these 821 firms, 23 percent were large firms with 500 or more employees, 14 percent of larger medium-sized firms with 250 to 499 employees, 20 percent of smaller medium sized firms with 100 to 249 employees, 13 percent of small firms with 50 to 99 employees, and 30 percent of very small firms with less than 50 employees. The covered diverse sectors range from agriculture to transportation, though there is a concentration in some sectors. The data consists of 25 percent of firms active in the information and communication sector, 16 percent manufacturers, 16 percent service providers of professional, scientific and technical services, 9 percent of firms offering private or public administrative services, and 35 percent of firms of all other sectors as financial service providers, education, and trade (see Table 4 in the annex).

Based on the matched data, a panel data set was compiled, which should contain firm information from 2016 to 2019 and the information on whether a company has published job ads referring to AI in specific terms as used to identify tier 1 ads before. For this dataset, further 100 companies had to be dropped because ORBIS information were available until 2015 only and thus did not cover our observation period. The comparison between both datasets revealed that this reduction due to missing information did not induce any further bias to our analytical panel dataset. In result, an analytical dataset of 2.476 firm-years was compiled representing 721 firms. Table 7 in the annex provides an overview over all variables. The panel is unbalanced, though for most firms the information is indeed complete: for three out of four firms, information from four years are available. For a minority of 55 firms, the measurement is available for one year only. Moreover, regarding the distribution over time, from 2016 to 2019, the measurements are evenly distributed, with around 600 observations in each year.

3.2 Identification strategy

Generically, we estimate the following structural model using panel regression techniques:

$$prod_{it} = \beta AI_{it-3} + \zeta x_{it} + c_i + u_{it} \quad (1)$$

where $prod_{it}$ is the productivity of firm i at time t. AI_{it-} refers some indicator of AI-use based on the job market data, which we by default lag by three years. x_{it} include observable controls. c_i captures time-constant unobserved heterogeneity and u_{it} is an indiosyncratic random error.

When testing H1, we are primarily interested in identifying the coefficient β, which measures the effect of AI on productivity. With respect to H2 (technological immaturity effect), we allow for interactions with the years

$$prod_{it} = \sum_{j=2016}^{2019} \beta_j AI_{it-3} + \zeta x_{it} + c_i + u_{it} \quad (2)$$

where, we now claim that β_j are increasing in j, i.e. $\beta_h > \beta_k$ for $h > k$.

H3 requires a slight variation of Eq. (1) in that we compare different time lags. In specific, we rerun Eq. (1) for the time lags $j = 1, \ldots 3$.

$$prod_{it} = \beta_j AI_{it-j} + \zeta x_{it} + c_i + u_{it} \quad (3)$$

H3 claims that $\beta_h > \beta_k$ for $h > k$.

The ability to identify the β-cofficients causally in Eqs. (1), (2) and (3) depends on the assumptions on c_i. We will generally allow that the unobserved heterogeneity term is correlated with the explanatory variables, which, if unaccounted, will cause omitted variable bias. To warrant a causal interpretation of the regression coefficients, we will run linear panel model fixed effects (FE) regressions. We assume a default time lag between offered jobs and ensuing productivity effects of three years in the baseline regressions. However, in order to test the investment hypothesis we vary this lag and also test for ranges from 2 to 4 years. The interest in the time varying effects is a further argument for using FE regressions, which retain only intra-unit temporal variance (Wooldridge 2002; Angrist/Pischke 2008; Brüderl, 2010). As a point of reference, we also report a random effects model.

Despite the ability to control for unobserved heterogeneity, our models also control for firm size measured as number of employees, year dummies and, were applicable, sectoral belonging. In order to assess the varying impact of the recruitment strategies over time, the interaction of measures of recruiting three years ago and the respective year dummy will be added. Several more interaction effects were tested.

4 Results

4.1 Descriptive insights into AI-skills demand in Finland

The employed job data provides the opportunity to get an overview of the development of the AI skills demand in Finland between 2013 and 2019. Figure 1 below shows the number of job ads differentiated by the different tiers and the total share of all these jobs ads in the number of total yearly job ads. We can see that the absolute number of AI related jobs increased until 2019 but lagged in growth compared to the total increase of jobs in the dataset.

We can also see that most of the job ads belong to the more general Tiers 2 and 3. The share of the more specialized skills has increased: the share of Tier 1 jobs has increased from 2.6% in 2013 to 6.5% in 2019, the share of Tier 2 from 29.4% in 2013 to 36.2% in 2019, while the share of Tier 3 jobs has dropped from 68.1% to 57.3% among all digital skill related job ads. This indicates a shift to increasing the adoption of AI in organizations.

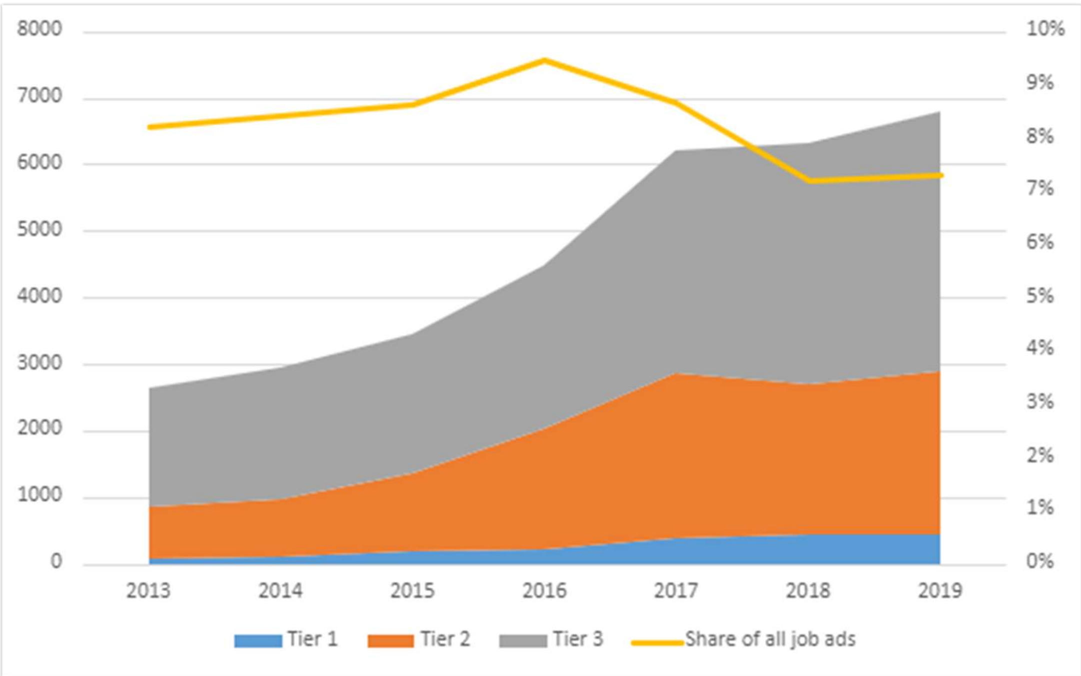


Figure 1: Number of jobs for the different sectors from 2013 to 2019 (left scale) and share of all jobs (right scale).

Focusing on the panel data and taking a firm perspective, similar trends were observed. First, the share of firms having published specifically AI related job ads increased from 2.3 percent in 2013 up to 13 percent in 2019. Thereby, the active firms offered on average two or three specifically AI related jobs in one year. Around half of the firms having advertised these jobs offered one AI job per year, while around 10 percent of the firms offered more than four jobs per year. The maximum was 45 jobs. However, it has to be noted that between 2013 and 2019, on average, no increase in the number of Tier 1 job offers per firm was observed for those looking for new AI skilled personnel (see Table 5 in the annex).

Secondly, the search for AI skill competences seems not be repeated often, over half for firms did search for the first time. Only in 2019, 70% of firms had hired at least once in a previous year, on average 1.5 times. Besides, most firms (75%) searched Tier 2 type of personnel before, increasingly over time from 50% in 2014 to 87% in 2019. The search for Tier3 seems to be quite unrelated. Most firms did hire before, however, still half of the firms searched before for tier3 but did nonetheless not search for Tier 1 type of qualification. Thus, Tier2 qualification might be a prerequisite of the demand of Tier1 jobs. In contrast, Tier 3 job search seems not to be linked in that way (see Table 6 in the annex).

Thirdly, in addition to the increase in the number of companies offering AI jobs over the years, the expected differences with regard to company size can be observed (see Figure 2). Over the entire period, larger establishments with at least 250 employees were more active than smaller establishments. It is also noticeable that in 2013, a quite comparable proportion of very small companies with less than 50 employees searched this kind of specialized personnel. However, the increase over the years has been much more dynamic in the other size groups, so that a clear size ranking can be seen today.

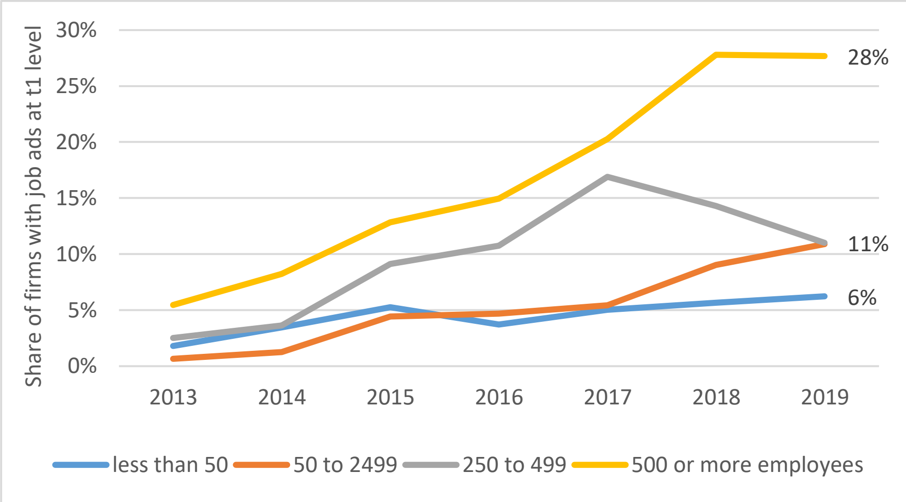


Figure 2: Share of firms from 2013 to 2019 having offered AI jobs, differentiated by firm size

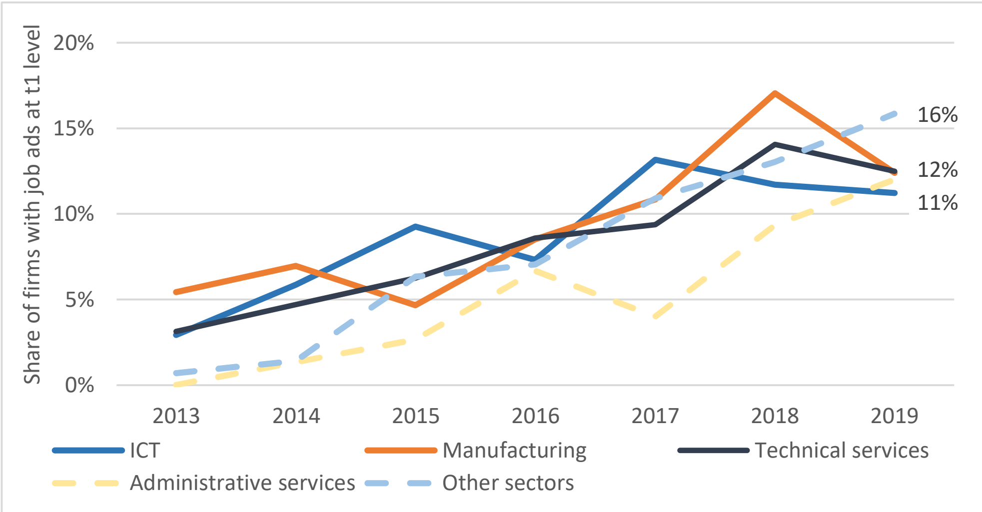


Figure 3: Share of firms from 2013 to 2019 having offered AI jobs, differentiated for the sector

Finally, still keeping this firm perspective, the data also show that the demand for -related competencies today does not differ that much among the sectors (see Figure 3). In 2019, around 12 percent of manufacturing firms offered -related jobs, as did 12 percent of administrative firms and professional service providers. In the ICT sector, only 11 percent of firms were searching for these competencies, while 15 percent of the firms of other sectorsinclude wholesale companies, construction firms, or insurance companies. Interestingly, the development started differently in the sectors; in 2013 the share of manufacturers offering at least one AI job offer (5%) was nearly double as high as in the ICT sector (3%) or among professional service providers (3%) in this time. This dynamic is also reflected in the peak for each sector. While a greater share of ICT firms was searching most in 2017, manufacturing firms as well as firms providing technical and scientific support did so in 2018, administrative and other firms in 2019.

4.2 The impact of AI on firm productivity

Turning to the hypotheses H1-H3, we analyzed the impact of the AI skills demand on the firms' productivity based on Eq. (1). Thereby, the focus lies on the most recent data with the financial information of 2016 to 2019 and the AI job ads offered in 2013 to 2016. The results referring to H1 and H2are displayed in Table 2 and Table 3. In all models, measures of the AI job offers lagged by three periods. The first two coloumns A and B in the left part of Table 2 display the estimated effects on productivity (operating revenues per employees) using a random and a fixed effects panel model. In general, we find a positive impact of the AI Job offer measures on productivity, were the fact that a firm had AI-related job offers increased productivity by about 44.000 euros per employee in the random effects model (A) and 42.000 euros per employee in the fixed effect model (B). Coloumn C repeats the FE approach using the number of AI-job ads as a continuous measure. The absence of significant effect here might indicate that already initial efforts to engage with AI might pay off, rather than that high intensities are needed. In fact, we have also probed this result by normalizing the number of AI-jobs with the total number of employees. Overall, corroborating H1 there seems to be evidence of a positive baseline effect of AI on productivity, even though intensities may play less of a role as long as any intended AI-related recruitment is observable.

With respect to H2, we claimed that AI may because of its novelty still be a premature technology, whose full potential unfolds only over time. This claim is analyzed in Coloumn D of Table 2 as well as Coloumns E, F and G in Table 3 all show extended results where we interacted the AI-measure by the year.

Table 1: Main regression results (linear panel regressions) of AI job offer impact on revenues per employees in 2016 up to 2019

Variables	(A)	(B)	(C)	(D)
	Random effects	*Fixed effects*	*Fixed effects*	*Fixed effects*
Medium sized firms (50-249 employees) (1)	**-81.49*****	**-99.53*****	**-100.6*****	**-97.66*****
	(22.54)	(23.84)	(23.87)	(23.81)
Larger firms (500 or more employees) (1)	**-125.3*****	**-153.5*****	**-156.5*****	**-152.9*****
	(33.14)	(35.93)	(35.96)	(35.87)
2017 (2)	**15.31***	**16.79***	**17.68****	**16.25***
	(8.667)	(8.656)	(8.662)	(8.803)
2018 (2)	**20.57****	**22.43****	**24.39*****	**22.79****

	(8.752)	(8.752)	(8.738)	(8.948)
2019 (2)	**36.31*** **	**39.25*** **	**41.67*** **	**33.32*** **
	(9.101)	(9.116)	(9.080)	(9.336)
AI related jobs offered (3)	**44.34** **	**42.80** **		-22.67
	(18.63)	(18.68)		(50.08)
Number of AI related job offers			0.612	
			(6.823)	
Manufacturing (C) (4)	**184.1** **			
	(91.53)			
Professional, scientific and technical services (M) (4)	69.81			
	(90.23)			
Administrative and support services; etc. (N O) (4)	16.88			
	(108.2)			
Other sectors (A to S) (4)	**409.4*** **			
	(72.78)			
Interaction year = 2017 x AI job				42.56
				(58.93)
Interaction year = 2018 x AI job				36.71
				(56.16)
Interaction year = 2019 x AI job				**123.6** **
				(55.28)
Constant	**230.4*** **	**431.7*** **	**433.7*** **	**432.1*** **
	(56.68)	(19.34)	(19.36)	(19.32)
N	2,460	2,460	2,460	2,460
Model test test-value (Wald resp. F-Stat)	71.60	7.066	6.174	5.691
Model test p-value	0,000	0,000	0,000	0,000
R2 within / between	0,024 / 0,040	0,024 / 0,006	0,021 / 0,006	0,029 / 0,005

Note: Coeff., SE in parentheses, N=2,460 (721 firms), # of data set per firms: 1-4, ~3.4 - Reference groups: (1) Small firms, (2) year 2016, (3) No AI related job offered, (4) Sector: J Information and communication, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Despite a positive baseline effect in Panels A and B of Table 4a, the effects depend on both cohort effects and firms' size. As panel D shows, the effects increase over time with a significant and positive effect (b=123.6, p<0.05) occurring in 2019. Moreover, the effects depend on the size of the company. The corresponding results are displayed in model E, F, and G in Table 3. Here we see that statistically significant effects are only observable for the group of large companies with more than 499 employees, while for both small and medium-sized firms there are no discernable effects.

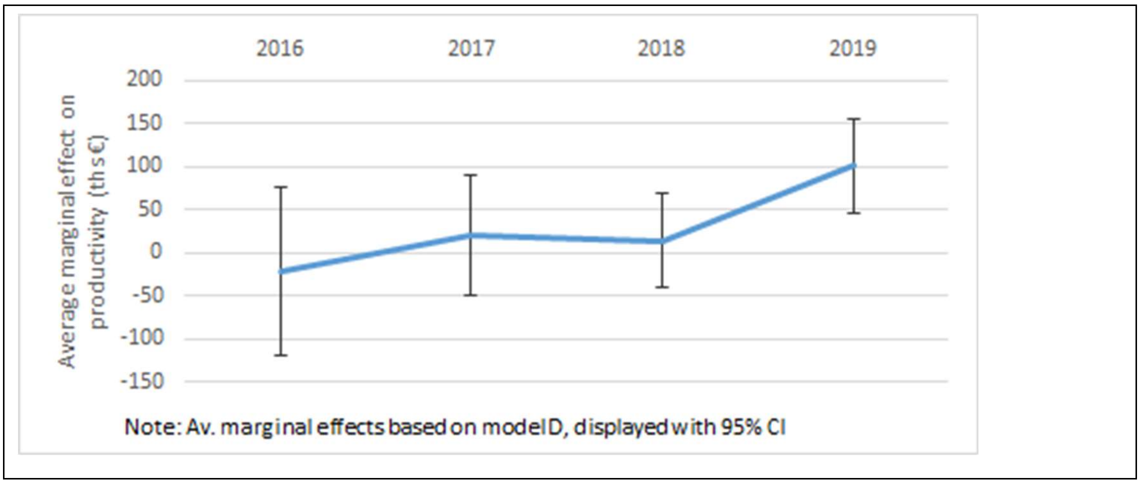
Table 2: Regression results (Fixed effects linear panel regressions) on revenues per employees in 2016 up to 2019 - size depending impact of AI job offer

Variables	(E)	(F)	(G)
	Small firms	*Medium-sized firms*	*Large firms*

2017 (1)	16.46	**25.55***	8.848
	(21.48)	(13.59)	(9.717)
2018 (1)	25.62	**24.65***	**26.08*****
	(21.99)	(13.65)	(10.06)
2019 (1)	**45.33***	23.02	**39.33*****
	(23.21)	(14.44)	(10.37)
AI related jobs offered (2)	27.77	62.92	**-78.49****
	(219.1)	(94.61)	(35.96)
Interaction year = 2017 x AI job	-6.014	-19.20	**91.03****
	(219.9)	(125.2)	(44.33)
Interaction year = 2018 x AI job	12.87	-71.54	**90.18****
	(235.6)	(105.4)	(42.12)
Interaction year = 2020 x AI job	-70.55	151.6	**117.6*****
	(242.7)	(103.4)	(40.92)
Constant	253.5***	367.5***	387.1***
	(15.08)	(9.938)	(6.950)
N	620	1,209	631
Model test (F value)	0.622	4.257	5.425
Model test p-value	0.738	0.000	0.000
R2 within / between	0.011 / 0.010	0.036 / 0.002	0.081 / 0.007

Note: Coeff., SE in parentheses, # of data set per firms: 1-4, ~3.4 - Reference groups: (1) year 2016, (2) No AI related job offered, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The statistically significant marginal effects by year of job offer in Panel D and G are visually presented Figure 4. In summary, we can corroborate H1 and H2, however, only for large firms, while the patterns are not statistically significant for small and medium-sized firms.



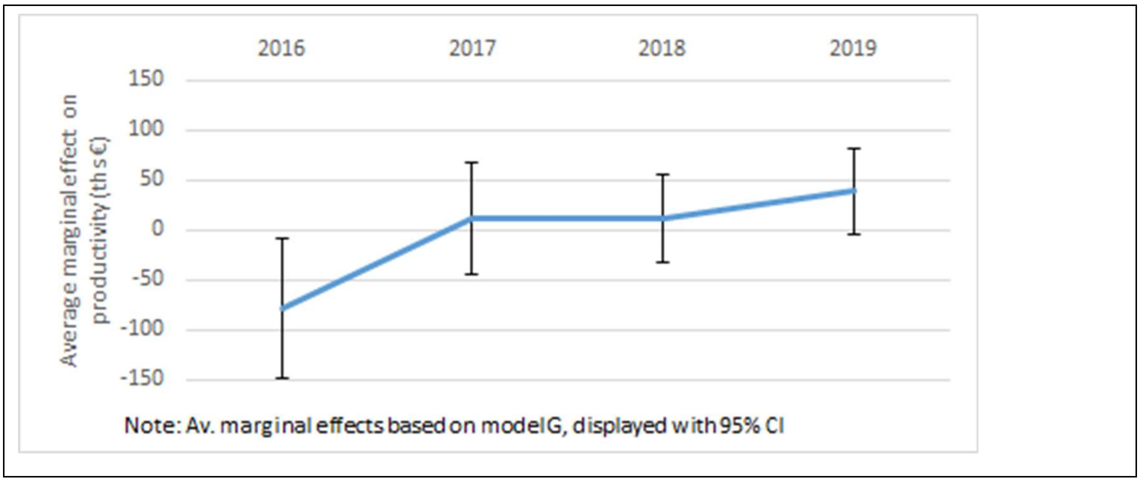


Figure 4: Marginal effects of having offered AI jobs three years prior between 2016 and 2019 (top: all firms, bottom: large firms).

Beyond these core results, a number of further observations related to Table 1 and Table 2 are worth noting. Firstly, based on the regression estimations of all models, there are two common results. On the one hand, it is obvious that productivity differs along the firm size. All factors taken into account, smaller firms show higher productivity than medium sized or larger firms do. On the other hand, for the period from 2016 to 2019 a steady increase in productivity on individual firm level is observable. Secondly, model A provides the well-known insight that productivity differs among industries. Our results indicate that manufacturing firms as well as firms of the group of other industries generated on average higher revenues per employee than firms in the information and communication sector did.

Having corroborated the positive baseline effects (H1) and technological maturity effects (H2) for large firms, we now turn to the investment delay effect in H3. To model this effect, we repeated the panel analyses by applying different time lags in Table 3 as described in Eq. (3). Besides firm size and time of placing the ad, the models included the indicator for having searched AI skills one year, two prior, and three years prior to the productivity measure. When looking at a one-year time lag, the estimators are calculated for job ads of 2015 onwards. When looking at a three-year time lag, data on AI job ads are available only for a period of three years.

Table 3: Main regression results (linear FE panel regressions) of impact on revenues per employees in 2016 up to 2019

Variables	(a)	(b)	(c)
	Time lag 3 years [(3)]	*Time lag 2 years* [(3)]	*Time lag 1 year* [(3)]

2019	**39.25***	**58.96***	**65.23***
	(9.116)	(9.980)	(10.17)
2018	**22.43**	**42.44***	**49.73***
	(8.752)	(9.598)	(9.843)
2017	**16.79***	**35.78***	**43.41***
	(8.656)	(9.543)	(9.754)
2016		**17.08***	**24.06**
		(9.491)	(9.751)
2015			7.728
			(9.664)
AI related jobs offered 3 years ago (1)	**42.80**		
	(18.68)		
AI related jobs offered 2 years ago (1)		-2.556	
		(15.95)	
AI related jobs offered 1 years ago (1)			0.808
			(13.15)
Medium sized firms (50-249 employees) (2)	**-99.53***	**-101.5***	**-85.74***
	(23.84)	(20.10)	(17.49)
Large firms (> 249 employees) (2)	**-153.5***	**-162.0***	**-155.0***
	(35.93)	(30.68)	(26.72)
Constant	**431.7***	**415.4***	**399.3***
	(19.34)	(16.51)	(14.70)
Observations	2,460	3,046	3,608
Model fit (F-test)	7.066	8.741	10.090
Sig	0.000	0.000	0.000
R2 within	0.0239	0.0260	0.0277
... between	0.0057	0.0053	0.0055

Note: Coeff., SE in parentheses. (1) No AI related job offered, (2) Small firms, (3) model a: year 2016, model b: year 2015, model c: year 2017, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Besides this strong result, an impact of the indicators on AI job offers was only detected with the longest three years' time lag as presented above. The estimated coefficients on the shorter lags in are not significant.

5 Conclusion

The presented results document the potential of this unique data. At first, the job data provides the opportunity to get an overview of the development of the AI skills demand during the last decade and allows the empirical review of several assumption on digitalization and AI: The development of the AI skills demand became clearly visible - from a job market point of view as well as from a firm or industry perspective. However, despite the game changing potential, the current demand for AI skills is still not very high. Only every eighth digitalizing firm, i.e., who were seeking digital competencies were active in this field. Thereby, sector specific differences became apparent. On the on hand, the pioneering role of ICT became clearly visible insofar as the demand in this sector was already saturated early on; a first peak was detected for 2015. The relatively high demand in the manufacturing sector, on the other hand, was a surprising result. In particular, the early greater activity level compared to the ICT sector is striking. However, this apparent advantage of the manufacturing sector is likely an artefact in that the data for the previous years is lacking and thus the early involvement of the ICT sector is not shown. Beyond this, however, the development over time reveals saturation for several groups. Noticeable here is the group of medium-sized companies, which showed a significant drop in demand after 2017. When viewed in this light, the findings for the manufacturing sector are just as striking. For this sector, the search for AI skills has been declining since 2018.

At second, further interesting insights could be gained when using panel analysis techniques. The technology maturity effect, i.e., the increasingly positive impact of AI job competencies on productivity over time, was clearly supported by our analyses. Companies that advertised AI jobs three years earlier were more productive than those that did not look for reinforcements in this field. This result became more prominent in 2018 and 2019. However, we detected interaction with firm size because significantly larger medium-sized firms do profit from their investment in new personnel with AI skills.

To conclude, the present analyses offer a first approach to the time-sensitive question of the changing influence of AI skill demands. Further analyses should refine these results to exploit the potential of the data fully. Furthermore, a comparative approach to the remaining digitization skills could be of interest.

CRediT authorship contribution statement

The authors are listed alphabetically. Here is the detail of the authors contributions. **Asta Bäck:** Data retrival, Text analysis & Natural Language Processing, Visualization. **Arash Hajikhani:** Conceptualization, Methodology - text analysis & natural language processing, visualization, Writing – original draft. **Angela Jäger:** Conceptualization, Methodology - econometric modelling, visualization, Writing – original draft. **Torben Schubert:** Conceptualization, Methodology - econometric modelling, Writing – original draft. **Arho Suominen:** Data retrival, Conceptualization, Writing – review & editing.

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Annex

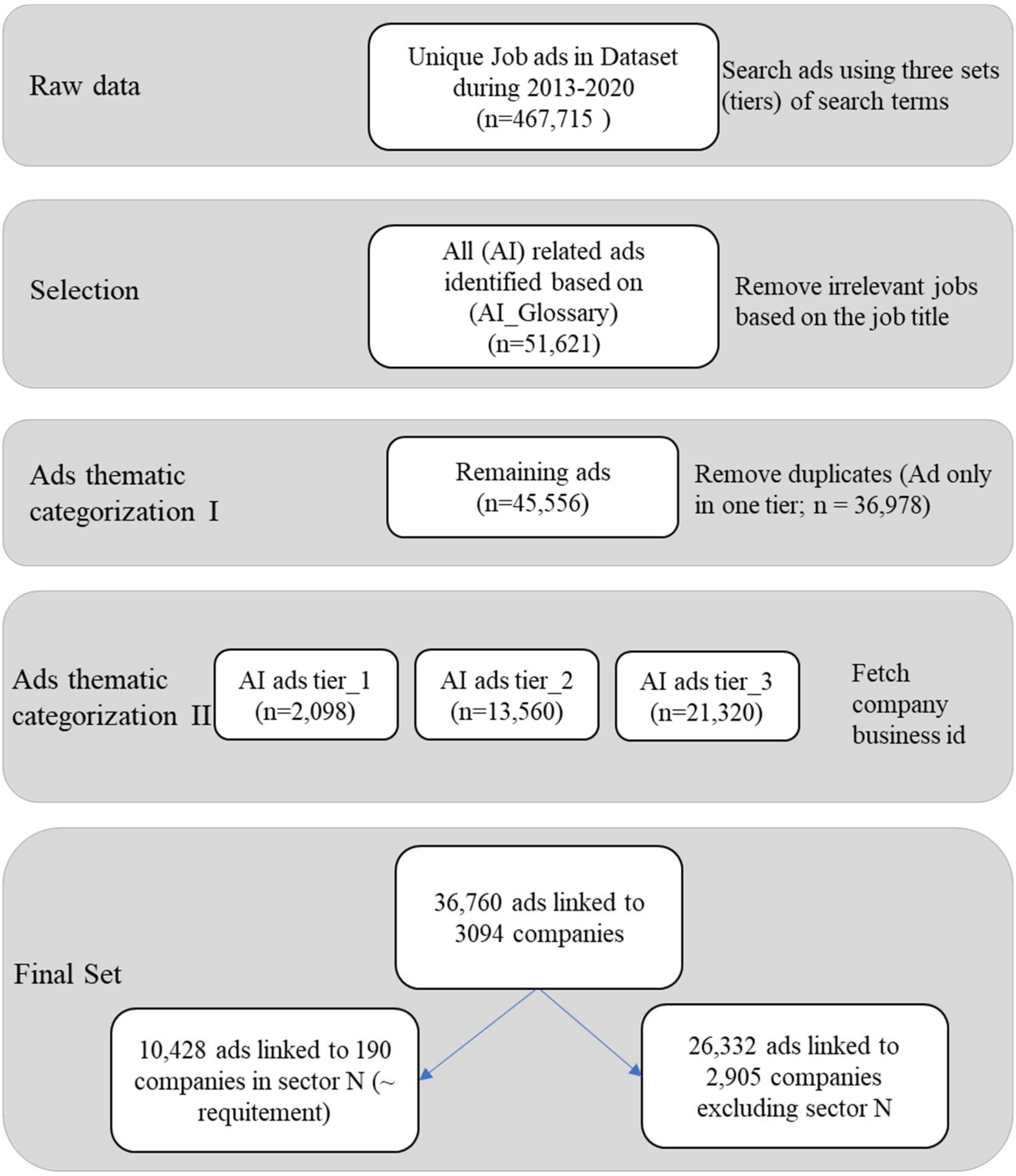

Figure 5: AI job offer data analytics process illustration

Table 4: Overview over firms in joint panel data on structural characteristics

Firm size (average over years)	Percent
Micro firms (<10 employees)	7.1
Small firms (<50 employees)	22.7
Low-medium firms (<100 employees)	13.5
Highly-medium firms (<250 employees)	19.6
Low-large firms (<500)	13.6
Highly-large firms (>499)	23.5

Sector groups	Percent
Information and communication	25.0
Manufacturing	15.7
Professional. scientific and technical	15.6
Administrative and support service incl	9.1
Others	34.6

Total (n = 821 firms)	100.0

Total (n = 821 firms)	100.0

Table 5: Overview over firms in joint panel data on job ads at level tiers 1

Year	Share of firms with T1 job ads	# of job ads per firm if searching
2013	2.3%	2.5
2014	3.9%	2.3
2015	6.5%	2.1
2016	7.6%	2.0
2017	10.6%	3.1
2018	13.2%	3.0
2019	13.3%	2.5
Total	8.2%	2.6

Table 6: Overview over firms in joint panel data on search experience before current t1 job offer

	Before this year, having searched skills of ...					
	Tiers 1 level		Tiers 2 level		Tiers 3 level	
Year	currently searching t1 skills	currently not searching t1 skills	currently searching t2 skills	currently not searching t2 skills	currently searching t3 skills	currently not searching t3 skills
2014	22%	2%	50%	16%	47%	28%
2015	32%	4%	74%	23%	70%	41%
2016	52%	6%	76%	31%	69%	53%
2017	52%	9%	78%	40%	78%	64%
2018	47%	14%	79%	51%	80%	74%
2019	71%	19%	87%	60%	84%	83%
Total	49%	7%	74%	31%	73%	48%

Table 7: Overview over variables used in multiple models

Variable		Mean	Std. dev.	Obs.	Firms
Based on OBRIS data					
	Sector				
nace_sonst	Other sectors	0.36	0.480	2460	721
nace_techn	M Professional, scientific and technical services	0.15	0.357	2460	721
nace_adminpublic	N O Administrative and support service incl defence	0.08	0.273	2460	721
nace_itcomm	J Information and communication	0.25	0.433	2460	721

nace_manufacturing	C Manufacturing	0.16	0.367	2460	721
empl	Firm size as # of employees [year]	1114.94	5336.508	2460	721
opre	Operating revenue (Turnover) th EUR [year]	358.659.90	1.552.470.00	2460	721
opreempl	Productivity as OPRE th EUR per employees [year]	365.21	748.89	2460	721
Based on AI job offer data					
t1	# of T1 job offers (job ads with generic terms referring to AI on vocabulary level) [year]	0.28	1.233	2460	721
t1_dum	t1 jobs (dummy)	0.12	0.321	2460	721
t1_lag3	# of T1 AI job offered 3 yrs prior	0.10	0.599	2460	721
t1_lag3_dummy	t1 jobs 3 yrs prior (dummy)	0.05	0.216	2460	721
t1_lag2	# of T1 AI job offered 2 yrs prior	0.15	0.789	2460	721
t1_lag2_dummy	t1 jobs 2 yrs prior (dummy)	0.07	0.256	2460	721
t1_lag1	# of T1 AI job offered 1 yr prior	0.23	1.131	2460	721
t1_lag1_dummy	t1 jobs 1 yr prior (dummy)	0.10	0.293	2460	721
t1exp	Previously hiring personal at T1 level (no. of years from 2013 on) [year]	0.27	0.700	2460	721
t1expd	Previously hired personal at T1 level [year]	0.17	0.373	2460	721