Master Thesis

Soft Skills, AI and Jobs

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Abstract

Artificial Intelligence (AI) is increasingly transforming the labor market, raising discussions over whether it will primarily substitute or complement human tasks. This thesis introduces a framework categorizing tasks into soft and hard skill-intensive, with the latter further divided into manual and non-manual categories. This is based on the idea that soft skill-intensive tasks require inherently human competencies which AI may complement, whereas hard skill-intensive tasks, especially non-manual ones, are more susceptible to substitution. Using US Census and Swiss job postings data spanning the past ten years, I examine the impact of AI adoption, proxied by AI-related job growth, on soft and hard skill intensities, defined as the share of tasks within an occupation that require each skill type. OLS regression results for the US show that 10,000 additional AI-related jobs are associated with an increase in the soft, and a corresponding decrease in the hard skill intensity, by 0.31 percentage points. This is confirmed by an instrumental variable analysis, suggesting a causal relationship. Surprisingly, the decline in hard skill intensity is driven by manual rather than non-manual tasks, which may indicate that the anticipated effects of AI on non-manual hard skill-intensive tasks have not yet materialized. The results for Switzerland, while less robust, point to a similar trend.

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1 Introduction

The recent, very rapid advances in Artificial Intelligence (AI) have led to extensive discussions about its impact on the labor market. While some argue that AI will largely complement the human workforce and boost productivity (e.g. The Times, 2024), others fear a massive job loss (e.g. The Wall Street Journal, 2024). Over the past 20–30 years of technological change, the arrival of the computer mainly substituted routine tasks, but complemented abstract, non-routine tasks (Autor et al., 2003). However, this distinction seems no longer applicable with an increasing adoption of AI, as it can perform not only routine, but also more complex, non-routine tasks. In this thesis, I therefore propose a new categorizaton of tasks that takes the capabilities of AI into consideration. Specifically, I differentiate between soft and hard skill-intensive tasks. This builds on the idea that soft skills refer to inherently human competencies, like creativity, critical thinking and communication, that are not easily replaceable in the near future. This finds support for instance by the most recent AI Index Report 2024 (Maslej et al., 2024), which, among other things, evaluates the performance of AI in comparison to humans in different fields. While it finds tremendous advances over the past years, AI still lacks behind in areas like abstract reasoning, empathy, or moral decision making in complex social scenarios. For the time being, a reasonable distinction of tasks with regard to their substitutability by technology could therefore be soft/ hard instead of routine/ non-routine.

Soft and hard skills do not have unique definitions. Soft skills, however, are more clearly defined, which is why I classify all tasks that are not soft skill-intensive as hard skill-intensive throughout this analysis. For the definition of soft skills, I draw on the US Occupational Information Network O*NET. It divides soft skills into social skills (such as negotiation, persuasion and social perceptiveness) and thinking skills (such as complex problem solving and critical thinking). O*NET does not provide a definition for hard skills, however they generally refer to teachable abilities that are specific to a particular job and typically quantifiable. They include a more general capacity to adapt and apply knowledge in different scenarios (Senger et al., 2024). Hard skill-intensive tasks thus include routine tasks, but go beyond that. Within hard skill tasks, I make an additional distinction between manual and non-manual tasks. The reason for this is that it seems possible that manual tasks, for instance those of construction workers, are not subject to substitution by AI yet. I therefore want to disentangle the two in order to be able to analyse them separately.

The main goal of this thesis is to investigate whether and in how far the increasing adoption of AI has already had an effect on the soft and hard skill task shares in the labor market. Since hard skill-intensive tasks, in particular the non-manual ones, seem more vulnerable to substitution, I would expect their share to decrease as AI expands. On the other hand, soft skill-intensive tasks could rather be complemented by AI, which is why their relative importance might increase. To test these predictions, I first calculate skill intensities for all occupations, and then use census data from the US between 2013 and 2022 and job market postings data from Switzerland between 2013 and 2023 to check whether the development of the skill intensities can be related to the number of AI-related jobs, my proxy for AI adoption. The US and Switzerland might be good choices for such an analysis, as they are both developed economies where the adoption of AI is, compared to other countries, more advanced. Both are also home to some of the best universities in AI-related research. With regard to the use of census and job market postings data, census data have the advantage of being representative at relatively small local levels, allowing for very detailed analyses. However, job postings have also been increasingly used in the recent literature, for instance by Acemoglu et al. (2022). Their main advantage is that they offer a timely representation of labor market trends. They may however be less representative, especially at a more granular local level, as not all job postings are publicly available.

My analysis begins with the determination of skill intensities for all occupations. Here, I use a task-based approach and classify all tasks of all occupations on O*NET into one of three categories: soft, hard (manual), and hard (non-manual). The skill intensities for each occupation are then determined as a weighted share of tasks in each category, where the weights are importance and relevance scores of tasks provided by O*NET. To give a few examples of the outcomes, according to this classification method, accountants have task shares of 35% soft, 0% hard (manual), and 65% hard (non-manual), teachers of 90% soft, 0% hard (manual), and 10% hard (non-manual), and plumbers of 16% soft, 69% hard (manual) and 15% hard (non-manual). After having calculated these shares, I merge them with the census data for the US and job market postings data for Switzerland. Doing this allows me to identify the skill intensities of an average worker in the US/ Switzerland and observe their evolution over time. The data show that the soft skill intensity of an average worker in both the US and Switzerland is around 50%, and that the hard skill intensity is split again almost equally between 25% manual and 25% non-manual. However, the countries differ in their trends. While the soft skill intensity steadily increased over time in the US, such a trend is not clearly visible in Switzerland. Additionally, the increase in the soft skill intensity in the US appears to be counterbalanced by a decrease in the manual, and to a lesser extent by a decrease in the non-manual hard skill intensity.

In a next step, I bring these developments in the skill intensities in relation to AI adoption. Following Bonfiglioli et al. (2024), I proxy AI adoption by the number of AI-related jobs. This is unfortunately not the most direct measure of AI adoption, and it potentially also captures broader technological advancements. However, more direct data, especially on a regional level, were to the best of my knowledge not publicly available at the time when I started this analysis. I therefore proceed with this proxy. I aggregate both the skill intensities as well as the number of AI-related jobs to the year-region level, where regions in my context are labor market areas. Then, I regress the skill intensities on the number of AI-related jobs. Importantly, I exclude AI-related jobs in the aggregation of the skill intensities to not have them included in both the dependent and independent variable. The results for the US show that the number of AI-related jobs is significantly related to the skill intensities. For instance, 10,000 additional AI-related jobs are associated with an increase in the soft skill intensity by 0.31 percentage points, and a decrease in the manual hard skill intensity by 0.32 percentage points in an OLS regression. Different from what was predicted, the number of AI-related jobs has almost no impact on the non-manual hard skill intensity. For Switzerland, the results are overall less significant, however there is a similar tendency towards an increase in the soft and a decrease in the manual hard skill intensity. The non-manual hard skill intensity even slightly increases with the number of AI-related jobs in the Swiss data.

To mitigate potential concerns about omitted variable bias and reverse causality, I additionally perform an Instrumental Variable (IV) regression. Specifically, I predict the number of AI-related jobs by the distance of a labor market area to the closest university that is strong in AI-related research. The idea behind it is that AI-related jobs are probably located near leading universities in this field. At the same time, the distance itself is unlikely to directly impact the skill intensities. For the US, the IV results strongly support the OLS results, with AI-related jobs being associated with an increase in the soft skill intensity, a decrease in the manual hard skill intensity and minimal change in the non-manual hard skill intensity. For Switzerland, the second stage is weaker, possibly due to the already less significant relationship in the OLS combined with a, compared to the US, weaker first stage.

Overall, my results show that AI adoption is indeed associated with an increase in the soft and a decrease in the hard skill intensity. For the US, the IV results even indicate that the relationship could be causal. However different from what was expected, the results show a decrease in the manual, and not in the non-manual hard skill intensity. One potential reason for this pattern could be related to my methodology, in particular the use of AI-related jobs as proxy for AI adoption. This likely also captures broader technological developments, such as process automation in the manufacturing industry. Beyond that, it could simply be too early to see the expected effects of AI in the non-manual hard skill intensity.

The remainder of this thesis proceeds as follows: Section 2 reviews the literature. Then, section 3 makes predictions about the outcomes using a theoretical model. Section 4 explains the data sources and gives descriptive evidence, followed by a description of the methodology in section 5. Section 6 presents the results and finally, section 7 concludes.

2 Literature Review

My thesis broadly relates to an extensive literature that deals with the impact of technological change on the labor market. While I particularly stress the early evidence on the impact of AI, I also briefly review the evolution of this literature in general. For this first part, I draw on an article by Autor (2022) and lecture notes by Dorn (2023). I then turn to a branch of the literature that highlights the role of soft skills in the labor market.

2.1 Technological Change Before AI

One of the first influential contributions to the study of technological change's impact on the labor market was made by Tinbergen (1974), who observed a growing wage inequality between skilled and unskilled workers, despite a steady increase in the supply of skilled labor. His explanation was that technological advancements were simultaneously driving up demand for skilled workers, thus counteracting the increase in their supply. This foundational work led to the *skill-biased technological change* framework which was investigated in a seminal paper by Katz and Murphy (1992). In their study, the authors empirically test the hypothesis that technological change increases demand for skilled workers more than for unskilled workers by comparing US workers with and without a college degree from 1963 to 1987. Their findings indeed show a positive and significant rise in the relative demand for skilled workers. The framework has been very successful in explaining real data, accounting for both the decline in the college wage premium in the 1970s and its sharp rise in the 1980s. Goldin and Katz (2008) further support the skill-biased technological change framework with evidence spanning the entire 20th century.

Despite its success in matching real data, the framework also has major shortcomings. First, it does not provide a mechanism explaining why technological change would increase the demand for skilled workers. Although this generally seems plausible, without understanding the mechanisms, scenarios where less skilled workers benefit more from technology are also possible. In addition, it is assumed that technology increases the productivity of all workers, only more so for skilled workers. However, evidence by Autor (2022) makes clear that technology cannot only complement workers to varying degrees, but also has the potential to substitute them. A third observation, brought forward by Autor et al. (2003), was that the impact of technology might primarily vary by occupational tasks, and not only by education. To address these limitations, Autor et al. (2003) developed a model of *task-biased technological change*.

The key idea behind task-biased technological change is that each occupation can be broken down into a subset of tasks, which can either be substituted, complemented or not affected at all by technological change. It was developed at a time that was highly influenced by the arrival of the computer. Importantly, the authors noted that computers were particularly good at performing routine tasks but had major difficulties accomplishing non-routine tasks. They thus assumed that routine tasks would be substituted by computers, while non-routine tasks, which for instance require problem-solving, creativity, or interpersonal interaction, would rather be complemented. Unlike the skill-biased technological change framework, the task-based model is able to explain why technology increases demand for skilled workers: they are typically better suited to perform non-routine tasks. Additionally, the task model captures more nuance. In some occupations, even highly educated workers might be replaced by technology if their tasks are routine and can be automated, while less educated workers in other roles might be complemented by technology if they perform non-routine tasks.

Besides the theoretical advantages, there is also strong empirical evidence for the task model. Autor et al. (2003) analyze the period between 1960 and 1998 in the US and find support for the hypothesis that the reduction in the price of computing capital has led to a reduced demand for routine labor and an increased demand for non-routine labor in industries that ex-ante (i.e. before the arrival of the computer) had a large share of routine tasks. Building on this research, the task model was subsequently expanded and investigated in greater detail. In particular, Goos and Manning (2007) made the interesting observation that routine jobs are usually found in the middle of the wage spectrum. As a consequence, the replacement of primarily routine task occupations leads to *job polarization*: an increase in employment in both low- and high-wage and a decrease in medium-wage occupations. Although the task model made great progress in understanding the impact of technological change on the labor market, it has an important limitation. It assumes that tasks are static and do not change over time. Only the allocation of workers and machines shifts, which would imply that workers concentrate on an ever decreasing number of tasks. In reality however, technology can also create new tasks.

The process of how technology displaces and creates tasks has been investigated by Acemoglu and Restrepo (2019). They identify three different channels through which technology affects labor demand. First, through a *displacement effect*, where tasks previously performed by workers are replaced by technology. This channel was already present in the original task model. They add the *reinstatement effect* which is the opposite of the displacement effect. The adoption of new technology immediately creates demand for new labor. An example would be a machinist who operates a newly adopted machine. Third, if technology increases the productivity, this can increase the demand for labor in non-automated tasks - a *productivity effect*. Thus, if technology creates sufficiently new tasks and increases the productivity, it may outweigh the negative effects caused by the displacement of labor. The analysis by Acemoglu and Restrepo (2019) finds that positive and negative employment effects were roughly balanced in a time period between 1947-1987, but that the displacement effect dominated the reinstatement and productivity effects in the more recent period between 1987-2017, at least in the United States. Autor et al. (2024) use patent data to find out how technology has influenced the labor demand. They similarly find that the substituting effects have intensified over the past four decades, while the augmenting effects became weaker.

2.2 Early Evidence on AI

A key question at the moment is in how far the era of AI changes the existing evidence. Already before the actual adoption of AI had started, scholars were interested to find out which occupations are likely to be most affected and developed several measures of AI exposure. With time and increasing adoption, the literature began to concentrate more on actual implications, in particular on employment and wages, but also on productivity.

2.2.1 Exposure

To identify AI exposure, most studies do not use clear-cut categories, like routine and non-routine. Rather, they for instance employ expert assessments to identify areas of high exposure. A first measure, by Felten et al. (2019), analyzes which abilities are affected by AI in the US. The authors define nine AI applications (such as image or speech recognition) and use crowdsourcing to identify how relevant these applications are to each of 52 abilities on O*NET. Based on this, they determine AI exposure for each occupation. Webb (2020) proceeds differently and performs an impact assessment on the task level. He measures overlaps between job task descriptions on O*NET and AI patents, with an higher overlap indicating higher AI exposure. A third measure, by Brynjolfsson et al. (2018), defines 23 features that determine the suitability of each occupational task for machine learning and uses crowdsourcing to derive an exposure score. Interestingly, the three measures make different predictions on which occupations are most exposed. While they mostly agree that managers and office staff are more, and farmers and construction workers are less exposed to AI, they for instance strongly disagree with regard to sales occupations. They also make different predictions with respect to income groups. Felten et al. (2019) forecast that the highest incomes are most affected by AI, while the lowest incomes are least affected. The Webb (2020) measure similarly predicts higher exposure for higher incomes, however suggests that top earners are somewhat less affected. In contrast, Brynjolfsson et al. (2018) find no major differences in exposures between wage groups. A more recent paper by Eloundou et al. (2023) examines the exposure with respect to Large Language Models (LLMs) and applies a mixture of human and GPT-4 ratings to make predictions at the task level. The authors conclude that approximately 19% of jobs in the US have at least 50% of their tasks exposed to LLMs. They also find larger exposure for higher incomes.

The exposure studies mentioned before have two limitations. First, they all focus on the US, and second, they cannot differentiate between substitution and complementarity exposure. Two other studies are on the global level and attempt to disentangle exposure effects. Gmyrek et al. (2023) let GPT-4 evaluate the exposure level of tasks and surprisingly find that the augmentation potential of AI is much higher than the automation potential (13% vs. 2.3% of total employment). They further conclude that the automation potential is higher in high- compared to low-income countries (5.1% vs. 0.4% of total employment) and stronger for females than for men, due to their higher presence in clerical jobs. However, I would be cautious not to overstate these results, as GPT-4 might be biased towards giving a rather optimistic outlook about its own future. The study by Cazzaniga et al. (2024) instead draws on Felten et al. (2019), but adds a measure of potential complementarity to it. They roughly find equal shares of automation and augmentation potential. They further conclude that the exposure is higher for more skilled workers, particularly due to their high augmentation potential.

Generally, the evidence on AI exposure seems to suggest that higher incomes are more exposed, both on the individual and the country level. Moreover, women seem to be more exposed. This evidence is different from the previous age of computerization, where mainly routine tasks of medium-wage occupations were affected. However, higher exposure for higher incomes does not necessarily imply that AI will reduce job polarization. As the study by Cazzaniga et al. (2024) suggests, higher incomes might also profit more from higher complementarity.

2.2.2 Employment and Wages

Agrawal et al. (2019) argue that whether substitution or complementary effects of AI dominate is open from a theoretical point of view. While AI is well-suited for improving prediction tasks, its role in the complementary process of decision-making is unclear. This suggests that AI could either increase the demand for human decision-making due to more and better predictions, thereby complementing human labor, or reduce the need for human input, leading to labor substitution. It is thus exciting to look at the early empirical evidence. I will begin with studies that focus on the firm level and then turn to studies on a more aggregate level.

Acemoglu et al. (2022) is one of the most prominent early studies. Using job postings data, they investigate the hiring behavior of firms relative to their AI exposure. They find that higher AI exposure is related with lower overall hiring at the establishment level in the US between 2010 and 2018 when using the Felten et al. (2019) and Webb (2020) exposure measures. With the Felten et al. (2019) measure for instance, a one standard deviation increase in AI exposure is associated with a 7.2% decline in non-AI employment. The relationship is less evident with the Brynjolfsson et al. (2018) measure. They additionally perform an analysis at the occupation and industry levels; however they do not detect any relationship between AI exposure and either employment or wages at these levels. They argue that it might be too early to see the effects. Conceptually similar is a study by Copestake et al. (2023). It also investigates employment impacts at the establishment level and uses job postings data, but focuses on the service sector in India. Their main finding is that a 1% increase in AI vacancy growth reduces non-AI vacancy growth by 3.61 percentage points, with the effect being larger for higher-skilled professional and managerial occupations. They futher analyze wage effects and find that a 1% increase in AI vacancy growth reduces the growth rate of non-AI median wage offers by 2.6 percentage points. Throughout their study, AI vacancies are instrumented by the Webb (2020) exposure measure.

Contrary to the previous findings are the results by Babina et al. (2024). This study takes a broader perspective on the firm's impact, and does not solely concentrate on labor. More precisely, it analyzes the impact of AI investments on several firm characteristics like firm growth, sales, market valuation and employment. Their findings show that higher AI investments are positively related with all firm characteristics, including employment. The authors consider several potential mechanisms as an explanation, but finally identify higher product innovation of AI-investing firms as a key driver for their results. Adding to the evidence on the firm level, the same authors find in a different study, Babina et al. (2023), that AI-investing firms employ more educated workforce, perform significant reorganization and flatten their hierarchichal structure.

The evidence at a more aggregate level is also mixed, though it tends to show negative effects. Bonfiglioli et al. (2024) perform an analysis on the level of commuting zones in the US and find negative employment effects in zones with higher AI exposure. The effects are in particular negative for low-skilled and production workers, while they are positive for high-skilled workers. This finding seems to contradict the previous observation that AI exposure is higher for higher wage groups. However, while indeed higher wage groups seem to be more exposed, their tasks tend to be augmented by AI. On the other hand, despite being less exposed in general, tasks of lower skilled workers are more likely to be substituted. This might explain these findings. It should be noted that this paper uses the same measure for AI exposure as I do in this thesis, employment in AI-related occupations, which might potentially also capture broader technological advancements. Huang (2024) uses a very similar approach, but constructs a measure of AI exposure on the level of commuting zones by combining survey data on industry-wide AI adoption with local industry employment shares. Despite using this measure, the overall results are very similar. Maybe interestingly, she further finds that the negative employment effects are more pronounced for men than for women. This again seems to contradict previous findings, e.g. from Cazzaniga et al. (2024), that women are more exposed. It should however be noted that the Felten et al. (2019) measure used in Cazzaniga et al. (2024) predicts a relatively strong exposure for clerical jobs, where women are overrepresented, but a relatively low exposure for production occupations, where men are overrepresented. These differences could thus arise from different measures of AI exposure.

The evidence by Albanesi et al. (2023) for Europe is more positive. Using the Felten et al. (2019) and Webb (2020) measures, the study finds higher employment for occupations that are more exposed to AI. Whether the more positive findings compared to the US can be explained by institutional differences or the design of the analysis is hard to say. But the authors caution against extrapolating these positive results into the future. Overall, it can be concluded that the majority of the existing evidence finds slightly negative employment and wage effects with higher AI exposure. However, the detailed impacts are still uncertain.

2.2.3 Productivity

I would also like to briefly highlight the literature addressing the productivity effects of AI. According to Acemoglu and Restrepo (2019), higher productivity could in principle be a driver of new employment, as discussed before. Most studies concentrate on the productivity effects of very specific occupations or tasks, and little is known about the overall labor market impacts so far. Brynjolfsson et al. (2023) study the productivity effects of a large number of customer support agents and find a productivity increase, measured by the resolved cases per hour, by 14% through the introduction of an AI-based conversational assistant. Peng et al. (2023) look at the occupational group of software developers and find astonishing effects. The treatment group, with access to AI tools, was able to complete a programming task 55.8% faster than the control group. Also professional writing can be improved with the help of AI, as Noy and Zhang (2023) document. They gave college-educated professionals writing tasks, and randomly exposed half of the group with access to Chat-GPT. Their average writing time decreased by 40%, while at the same time output quality, evaluated by experienced professionals, increased by 18%. Other research shows that AI can even increase productivity in creative tasks, e.g. ideas generation (Girota et al., 2023). However, there might be limitations. Dell'Acqua et al. (2023) study the productivity effects of consultants exposed to AI, but provide them with tasks inside and outside the current frontier of AI capabilities. While their productivity increased for tasks inside the frontier, it decreased for those outside of it. They conclude that it is important to be aware of the capabilties of AI for the productivity effects to materialize.

There is less evidence on whether the positive effects observed for specific tasks or occupations transfer to the labor market at large. An exception is Haslberger et al. (2023) who take a representative sample of the UK working-age population and expose a treatment group to Chat-GPT. They indeed find that overall productivity increased with the help of AI. Unclear however is whether these productivity increases positively impact employment. Acemoglu et al. (2022) could not find evidence for this in their study. On the other hand, the work of Babina et al. (2024) points towards these effects. But they both note that productivity effects of AI are hard to identify as the characteristics of adopting and non-adopting firms strongly differ.

2.3 The Role of Soft Skills

In addition to the literature on technological change, my thesis relates to studies that deal with the role of soft skills in the labor market. Since there is no general definition, studies differ in how they define and measure soft skills. Many also distinguish between cognitive and non-cognitive skills, which is related to, but often different from the distinction between soft and hard skills. Studies further differ in their focus. A first branch of the literature takes the perspective of an individual and investigates in how far soft skills lead to higher employment and wages. Closer to my thesis is a second branch that analyzes broader labor market developments, e.g. whether the amount of soft skill-intensive occupations has increased over time.

A study by Heckman and Kautz (2012) looks at how individual soft skills determine future life outcomes. It finds that strong soft skills lead to higher educational attainment, higher earnings, better health, and lower criminal activity. Several additional studies confirm that a higher level of soft skills leads to higher earnings (e.g. Kuhn and Weinberger (2005) for leadership skills in the US, Edin et al. (2022) for non-cognitive skills in Sweden, and Langer and Wiederhold (2023) for social skills in Germany). Heller and Kessler (2022) argue that within soft skills, communication skills are in highest demand by employers and yield the highest returns, while being a team player or being respectful did not contribute to better outcomes in their setting. Two other studies focus in particular on the interplay between cognitive and non-cognitive skills: Weinberger (2014) highlights the complementarity between the two and finds highest employment and wage growth for workers that are strong in both areas. Slightly differently, Lindqvist and Vestman (2011) shows that while low non-cognitive skills are a stronger predictor of poor labor market outcomes, high cognitive skills, on the other hand, better predict positive outcomes. Overall, and perhaps unsurprisingly, all studies agree that strong soft skills are advantageous in the job market.

Regarding the literature that analyzes broader labor market developments, Deming (2017) is probably closest to my thesis. His key finding is the growing importance of social skills. Specifically, he concludes that the share of social skill-intensive occupations grew by 11.8% percentage points between 1980 and 2012 in the US, while the share of STEM jobs, in particular those that do not additionally require social skills, at the same time decreased by 3.3 percentage points. A similar pattern is visible with respect to wage growth. He points out that these findings may be explained by the fact that computers cannot replace human interaction so far, however without testing this empirically. My work differs from his in two important ways: first, I use the broader notion of soft skills, which includes thinking skills in addition to social skills. And second, I empirically test the relationship between soft skills and technological development. Related research, e.g. Atalay et al. (2020), Hansen et al. (2021) and Borghans et al. (2014), confirms the increasing importance of soft skills. This trend is also reflected in job market postings, as Lyu and Liu (2021) document for the US energy sector. However, the contribution of soft skills to firm productivity shows mixed results. While Deming and Kahn (2018) find a positive contribution of soft skills, Lyu and Liu (2021) do not.

There is only a small branch of the literature that analyzes the relationship between soft skills and technological change more specifically. Kiener et al. (2023) investigate in how far social skills prepare workers with respect to the digital transformation in Switzerland. Overall, they cannot confirm the hypothesis that workers with a high level of social skills benefit more from technological progress. However, they do find additional benefits for workers with social skills in more specialized occupations. Using Italian job market postings, Colombo et al. (2019) examine which occupations, differentiated by soft and hard skill intensity, are more likely to be automated. They find that jobs requiring a high level of either soft or hard skills are less susceptible to automation, meaning that strong proficiency in either type is sufficient to reduce the risk of automation.

To conclude, soft skills play an important and increasing role in the labor market. This holds at the individual level, where the literature finds higher earnings for workers who possess a higher level of soft skills, but also at the market level, where the share of soft skill-intensive occupations has grown over time. The relationship between soft skills and technological change has not been the focus of many studies. There are indications that workers with a high level of soft skills are better protected against the risk of automation, but whether technological change actively shapes the demand for soft skills over time has, to the best of my knowledge, not been investigated so far.

3 Model

Before I begin with my empirical analysis, I want to make some predictions with the help of a theoretical model. To do this, I use a production function that assumes that output can be produced with either soft skill (L_S) or hard skill labor (L_H). Within hard skill labor, I further differentiate between manual ($L_{H,M}$) and non-manual hard skill labor ($L_{H,N}$):

$$Y = [\alpha(L_S)^\rho + (1-\alpha)(L_H)^\rho]^{\frac{1}{\rho}}\,, \tag{1}$$

$$\text{where} \quad L_H = (L_{H,M})^\beta \, (L_{H,N} + \theta \, AI)^{1-\beta} \tag{2}$$

This form assumes that non-manual hard skill labor and AI are perfect substitutes, wherby θ adjusts for the effectiveness of AI. I further assume a Cobb-Douglas form within the two hard skill categories and a more general CES form between soft and hard skill labor. This is mainly because I want to concentrate on the effects between soft and hard skill labor and at the same time simplify notation. The goal is to make predictions on how AI is likely to affect each of the three labor inputs. To gain insights on this, I derive the cross derivatives of the production function, first with respect to each labor input, and then with respect to AI. The detailed derivations can be found in the appendix.

The first derivatives of Y with respect to the labor inputs $L_S, L_{H,M}$ and $L_{H,N}$ can be derived as follows:

$$\frac{\partial Y}{\partial L_S} = \alpha \, Y^{1-\rho} \, L_S^{\rho-1} \tag{3}$$

$$\frac{\partial Y}{\partial L_{H,M}} = (1-\alpha)\,\beta\, Y^{1-\rho}\, L_H^{\rho-1}\, L_{H,M}^{\beta-1}\,(L_{H,N} + \theta\, AI)^{1-\beta} \tag{4}$$

$$\frac{\partial Y}{\partial L_{H,N}} = (1-\alpha)(1-\beta)\, Y^{1-\rho}\, L_H^{\rho-1}\, L_{H,M}^{\beta}\,(L_{H,N} + \theta\, AI)^{-\beta} \tag{5}$$

Based on these derivatives, I derive the cross derivatives. The cross derivative of Y with respect L_S and AI is:

$$\frac{\partial^2 Y}{\partial AI\, \partial L_S} = (1-\rho)\alpha(1-\alpha)(1-\beta)\,\theta\, Y^{1-2\rho}\, L_S^{\rho-1}\, L_H^{\rho-1}\, L_{H,M}^{\beta}\,(L_{H,N} + \theta\, AI)^{-\beta} \tag{6}$$

Under the reasonable assumption that soft and hard skill labor are complements (i.e. $\rho < 0$), this derivative is strictly positive. This means that an increasing use of AI increases the marginal product of soft skill-intensive labor. It is thus likely that the share of soft skill labor in the production process increases.

The cross derivative of Y with respect to $L_{H,M}$ and AI is:

$$\frac{\partial^2 Y}{\partial AI\, \partial L_{H,M}} = A + B + C, \tag{7}$$

where

$$A = (1-\rho)(1-\alpha)^2\beta(1-\beta)\theta Y^{1-2\rho} L_H^{2(\rho-1)} L_{H,M}^{2\beta-1}\,(L_{H,N} + \theta AI)^{1-2\beta}\,, \tag{8}$$

$$B = (\rho-1)(1-\alpha)\beta(1-\beta)\theta Y^{1-\rho} L_H^{\rho-2} L_{H,M}^{2\beta-1}\,(L_{H,N} + \theta AI)^{1-2\beta}\,, \tag{9}$$

$$C = (1-\alpha)\beta(1-\beta)\theta Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta-1}\,(L_{H,N} + \theta AI)^{-\beta}\,. \tag{10}$$

Here, C is always positive and, again assuming $\rho < 0$, A is positive and B negative. Thus, the overall sign of the derivative is theoretically ambiguous. But since B would need to be very negative to outweigh the positive contributions of both A and C, the term as a whole is more likely to be positive. A positive term would imply that an increasing use of AI raises the marginal product of manual hard skill labor.

Finally, the cross derivative of Y with respect to $L_{H,N}$ and AI is:

$$\frac{\partial^2 Y}{\partial AI\, \partial L_{H,N}} = D + E + F, \tag{11}$$

where

$$D = (1-\rho)(1-\alpha)^2(1-\beta)^2\theta Y^{1-2\rho} L_H^{2(\rho-1)} L_{H,M}^{2\beta}\,(L_{H,N} + \theta AI)^{-2\beta}\,, \tag{12}$$

$$E = (\rho-1)(1-\alpha)(1-\beta)^2\theta Y^{1-\rho} L_H^{\rho-2} L_{H,M}^{2\beta}\,(L_{H,N} + \theta AI)^{-2\beta}\,, \tag{13}$$

$$F = -(1-\alpha)(1-\beta)\beta\theta Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta}\,(L_{H,N} + \theta AI)^{-\beta-1}\,. \tag{14}$$

In this case, F is always negative, and keeping the assumption of $\rho < 0$, D is positive and E negative. Despite being theoretically ambiguous again, the sign is more likely to be negative, meaning that an increase in the use of AI more likely reduces the marginal product of non-manual hard skill labor.

In summary, I derive the following predictions from the model:

- The cross derivative of output with respect to soft skill labor and AI is strictly positive, i.e. both are complements. I thus predict an increasing use of soft skill labor in the production process as AI adoption increases.
- Manual hard skill labor is likely complemented by AI, as indicated by the more likely positive cross derivative. As a consequence, I expect an increasing use of manual hard skill labor in the production process, however, due to the theoretical ambiguity of the model results, with less certainty.
- Non-manual hard skill labor is likely substituted by AI, as indicated by the more likely negative cross derivative. I thus expect a decreasing role of this labor input in the production process with increasing AI adoption.

4 Data and Descriptive Evidence

In this section, I describe the data I used and give some descriptive evidence. I begin with explaining how I determined the skill intensities of each occupation, and then turn to my additional data sources, US Census data and Swiss job market postings.

4.1 Skill Intensities

To calculate the skill intensities of each occupation, I use a task-based approach. Broadly, I classify each task into one of three categories (soft, hard (manual), hard (non-manual)) and then determine the skill intensities of an occupation as the percentage of tasks in each category.

In more detail, I proceed as follows: I first download task statement files for the years 2013–2023 from the resource center of the US Occupational Information Network O*NET. I consistently use the database versions ending with .0 (versions 18.0-28.0) that are published in August every year, in total 11 files. The exact number of tasks slightly changes every year, but overall there are roughly 19,000 tasks describing around 900 occupations. For each task in every file, I extract the key action verbs. I chose to do the classification of tasks based on action verbs, first because I believe that they best describe the essence of a task. And second, because I considered it to be more transparent to classify actions verbs compared to task statements as a whole. Most tasks have either one or two action verbs, however there are a few with more. The maximum number for a single task statement in my observation period is nine. Action verbs, as I define them, are not all verbs of a task statement. In particular, they do not include verbs that describe the purpose of the task. To illustrate this point, here is an example task statement: "Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency." In this case, "direct" and "coordinate" would count as action verbs, but "fund", "maximize" and "increase", that describe the purpose of the task, would be ignored.

Table 1: **Soft Skills** (Source: O*NET)

Soft Skill	**Description**
	Social Skills
Coordination	Adjusting actions in relation to others' actions.
Instructing	Teaching others how to do something.
Negotiation	Bringing others together and trying to reconcile differences.
Persuasion	Persuading others to change their minds or behavior.
Service Orientation	Actively looking for ways to help people.
Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Thinking Skills
Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making.
Active Listening	Giving full attention to what others are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.
Judgment and Decision Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.
Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.
Monitoring	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.
Time Management	Managing one's own time and the time of others.

After having extracted the action verbs, I classify them into one of the three categories mentioned before: soft, hard (manual), hard (non-manual). Since I do this classification manually and I am aware that some classification decisions might depend on my subjective reasoning, I try to proceed as objectively as possible. For the classification as soft, I draw on the soft skill definition from O*NET. It includes 14 categories, divided into social and thinking skills, which are presented in Table 1. For every action verb, I check in detail whether it fits into one of these categories, and, if I classify an action verb as soft, argue which category I considered applicable. For the classification within the hard skill categories, hard (manual) and hard (non-manual), I check whether the verb describes a process that involves manual activities. While the majority of verbs can be classified directly, there are several cases where the classification depends on the context and the verb itself is not informative enough. An example is the verb "maintain". It could for instance appear in a context like "to maintain a relationship", or alternatively in a context like "to maintain a database". The first case would clearly describe a soft skill-intensive action, while the second would rather be hard skill-intensive. In these cases, I differentiate between contexts that the action verb can appear in and categorize accordingly. At the end of this process I have 1,361 action verbs in total, of which I classify 336 as soft, 702 as hard (manual), and 323 as hard (non-manual).

The next step is to classify the tasks based on the classification of the action verbs. I proceed by counting the number of action verbs in each category for every task, and then assign the category with the highest number of action verbs to the task. For instance, if I assigned two soft skill verbs and one hard skill verb to a task, the task as a whole would be classified as soft. However, there are situations where there is no unique category with the highest number of action verbs. I resolve these cases by introducing the following hierarchy: 1. soft, 2. hard (manual), 3. hard (non-manual). The assumption behind it is that if a task includes for instance the same number of soft and hard skill actions, soft skill actions are more important for the completion of the task. This allows me to uniquely classify all tasks. It is possible that this approach introduces a small bias with respect to soft skill-intensive tasks. However, I regard this as acceptable to not complicate the classification process. Following this approach, out of 19,281 tasks in total in 2023, I classify 9,587 as soft, 5,438 as hard (manual), and 4,256 as hard (non-manual).

As a final step, I calculate the skill intensities of an occuaption as the percentage of tasks in each category. This however assumes that all tasks are equally important. In reality, some tasks might be more important than others, which I want to capture in the calculation of the skill intensities. O*NET provides importance and relevance scores for the large majority of tasks in their task rating files. These scores result from surveys of professionals who were asked to rate how relevant and important tasks are to their occupation. I use these scores and calculate weighted skill intensities according to the following formula:

$$\text{Weighted Skill Intensity}_{I_k} = \frac{\sum_{i \in I_k \subseteq J_k} (\text{Importance}_i \times \text{Relevance}_i)}{\sum_{i \in J_k} (\text{Importance}_i \times \text{Relevance}_i)} \tag{15}$$

Here, i denotes an individual task, J_k is the set of all tasks within occupation k, and $I_k \subseteq J_k$ is the set of tasks in a specific skill category (soft, hard (manual), hard (non-manual)) within occupation k. Since all three categories again add up to 100%, the interpretation is the same as for the unweighted intensities: they reflect the relative emphasis of a skill category, only additionally weighted by importance and relevance. There are a few cases where no importance and relevance scores are available. A first case is when no scores are available for any tasks in an occupation. In this case, I do not perform any weighting. A second case occurs when only some tasks of an occupation have missing scores. Here, I differentiate two further scenarios. If all tasks of a category (soft, hard (manual), hard (non-manual)) have missing entries, I use the average importance and relevance score for that category across all occupations. If only some tasks in the category have missing entries, I use the average score for that category within the same occupation.

As a result, I finally receive weighted intensities as percentages for all occupations. In the majority of cases the difference between weighted and unweighted intensities is not very large and amounts only to a few percentage points. However, I decide to make use of this additional information and proceed with the weighted intensities. In the following, I will only use weighted skill intensities and refer to them just as skill intensities.

Figure 1: **Skill Intensities by Occupational Group in 2023**

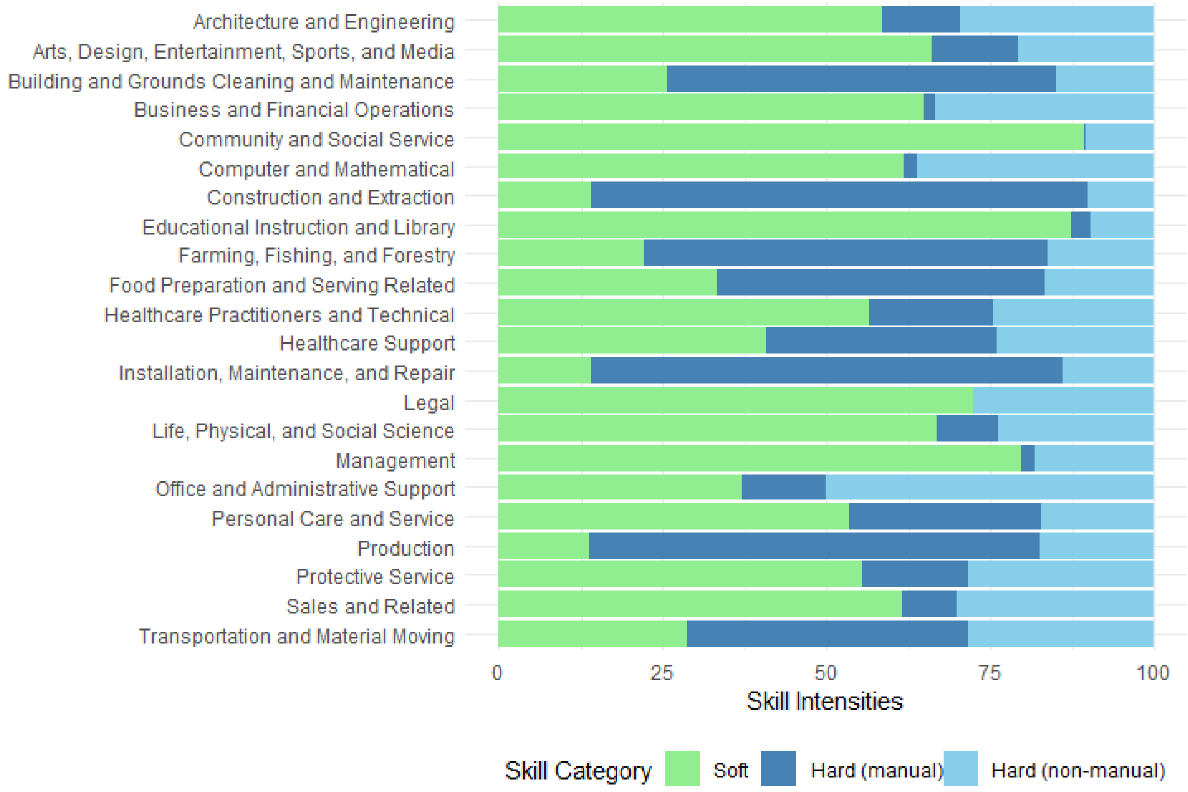


Figure 1 depicts the skill intensities for various occupational groups in 2023. It is calculated by taking the simple average of all occupations within an occupational group, and does not include how many people actually work in a specific occupation. I will add this information later, when I merge the skill intensities with US Census and Swiss job market postings data. The chart shows that the occupational groups with the highest soft skill intensities are Community and Social Service (89%), Educational Instruction and Library (87%) and Management (80%). In contrast, the lowest soft skill intensities are observed in highly manual occupations, particularly Construction and Extraction (14%), Installation, Maintenance, and Repair (14%) and Production (13%). The skill intensities in the hard (non-manual) category are slightly less volatile across occupational groups, with the highest share of tasks in this category found in the Office and Administrative Support group (50%).

To be assured that the skill intensities I receive via this task-based approach are indeed reasonable, I perform a crosscheck with importance scores that are provided by O*NET. More precisely, O*NET has importance scores for each soft skill category from Table 1 on the occupational level which are derived from surveys. I compare, for each occupation, the average importance score across all soft skill categories with my soft skill intensities and find a correlation coefficient of 0.82. This suggests that my approach produces very similar results regarding which occupations are more or less soft skill-intensive. A valid question in this context is why I chose not to rely on those scores in the first place and instead decided to calculate my own skill intensities. One important consideration was the conceptual background of the task model which motivated me to classify each task indivdually. Additionally, the scores on O*NET are based on surveys with a relatively small sample size, and I considered it to be more transparent to develop a more grounded approach. Finally, my skill intensities differ from the scores on O*NET in that all skill categories must sum to 100%. This means that when an occupation becomes more soft skill-intensitve, it necessarily becomes less hard skill-intensive. By contrast, with the importance scores on O*NET, all categories can increase or decrease in importance simultaneously. While this can certainly be the case in reality, I considered it to be more insightful to investigate the skill intensities in relative terms.

4.2 US Census Data

For my analysis of the US, I use, in addition to the skill intensities, census data from the Integrated Public Use Microdata Series (IPUMS USA) (Ruggles et al., 2024). Specifically, I draw on the annual American Community Survey (ACS) for all years between 2013 and 2022. The ACS is a nationwide survey that is conducted by the US Census Bureau. A key advantage of this data set is that it is microdata, i.e. on the level of an individual person, which allows very granular and detailed analyses. To ensure representativeness for the whole US population, each person in the data set is associated with a person weight which I consistently make use of throughout my analysis. IPUMS provides a broad range of different variables for download. My data extract includes in particular personal information, such as sex, age, educational attainment, and place of residence, as well as labor market information, such as employment status, occupation, industry, and place of work. I exclude Puerto Rico as well as oversea territories due to limited data availability.

Next, I map the skill intensities to the census data. Naturally, I can only map the skill intensities for employed people, and not for people who are unemployed or not in the labor force. I therefore only use the whole data set for the calculation of several control variables, which are described in more detail in the methodology section, but use a reduced data set for the analysis of skill intensities. Adding the skill intensities to the census data requires an additional step, because the occupational codes used in the ACS are more aggregated than those on O*NET. O*NET distinguishes between approximately 900 occupations, whereas the ACS includes only about 500. I therefore create a mapping between the two and calculate the skill intensities for the adjusted set of occupations.

After having added the skill intensities for all employed individuals, I am in the position to aggregate and spot trends in their development. Table 2 shows the development of skill intensities aggregated on the yearly level. In general, changes can arise from two sources. The first is workers shifting from one occupation to another, which is captured through the use of census data. The second is changes in tasks within occupations, which are captured by my method of calculating the skill intensities of occupations for each year individually. Due to the relatively short time period of ten years, the first channel is probably much more important. As Table 2 shows, the tasks of an average

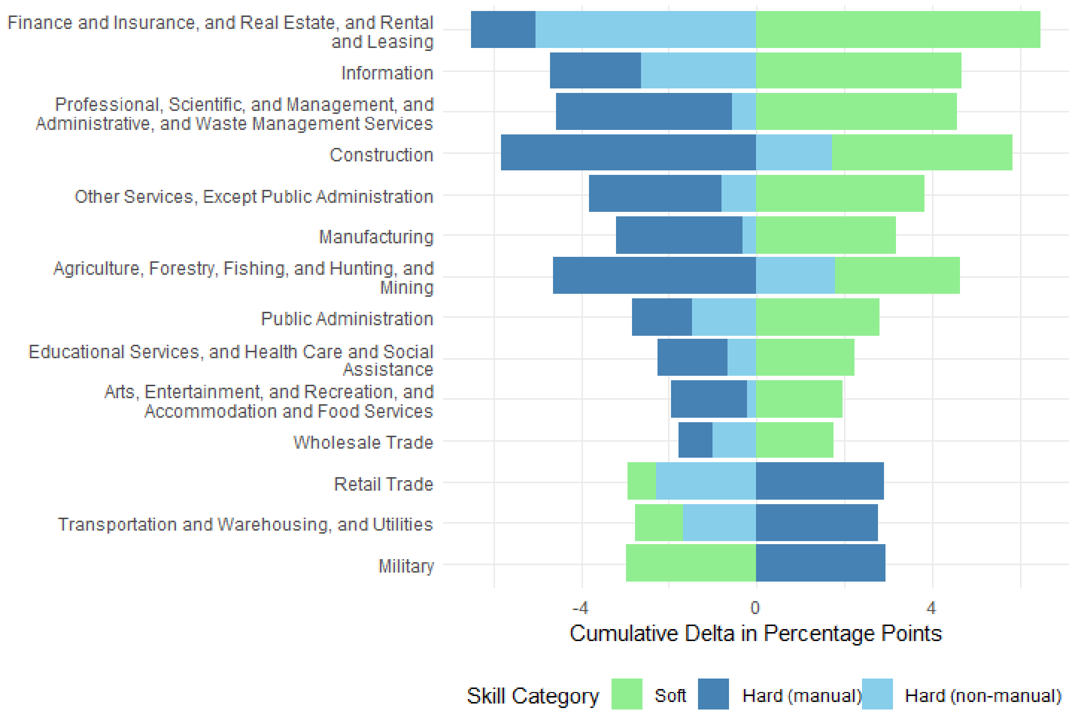
Table 2: **Development of US Skill Intensities and AI-Related Jobs**

Year	Soft	Hard (manual)	Hard (non-manual)	AI-related Jobs
2022	49.9%	25.7%	24.4%	6.7M
2021	49.4%	26.1%	24.5%	6.3M
2020	49.5%	26.0%	24.6%	6.2M
2019	48.8%	26.7%	24.5%	5.7M
2018	48.4%	26.8%	24.8%	5.5M
2017	48.2%	26.6%	25.1%	5.2M
2016	48.0%	26.9%	25.2%	5.0M
2015	47.8%	27.1%	25.2%	4.7M
2014	47.6%	27.3%	25.2%	4.5M
2013	47.2%	27.4%	25.3%	4.3M

US worker are almost equally divided between soft and hard skill-intensive tasks, both with a share of about 50%. The hard skill share again almost equally divides into manual and non-manual tasks. Beyond that, it is clearly visible that the soft skill intensity has increased over time. While it only amounted to 47.2% in 2013, it increased to 49.9% in 2022. Although this change might seem small, I consider it quite large given that it is the average intensity across the whole US population. The trend also seems to be relatively stable, with steady increases every year. The table further shows that the increase in the soft skill intensity is largely offset by a decrease in manual hard skill tasks, and only to a smaller extent by a decrease in non-manual hard skill tasks.

It is also interesting to see in how far the development of skill intensities differs across industries. Figure 2 shows the cumulative delta of US skill intensities for different industries over the whole observation period. For each industry, positive and negative deltas have to add up to zero, which implies that the bars to the left and to the right of zero must have equal length. The chart is ordered by the delta in soft skill intensity in descending order. By far the strongest cumulative increase in the soft skill intensity is visible for the finance industry (+6.5 percentage points), followed by the information industry (+4.7 percentage points). Overall, almost all industries experienced an increase in the soft skill intensity, with only a few exceptions. The military industry as depicted here might not be representative, as O*NET does not include military occupations. Thus, this category only includes non-military occupations in the military industry. The increase in the soft skill intensity is largely counterbalanced by a decrease in the manual hard skill intensity, as already seen before. It will be interesting to find out whether these developments can be causally related to the rise of AI in my subsequent regression analysis. At least the correlation between the soft skill intensity and the number of AI-related jobs appears to be positive: the census data indicate an increase in the number of AI-related jobs from 4.3 to 6.7 million, as shown in Table 2. I explain in the methodology section which occupations I regard as AI-related. It should be stressed that these absolute numbers pertain to the entire US population and not just the census sample, which is due to the incorporation of the person weights provided in the data.

Figure 2: **Cumulative Delta of US Skill Intensities by Industrial Group 2013-2022**



4.3 Swiss Job Market Postings

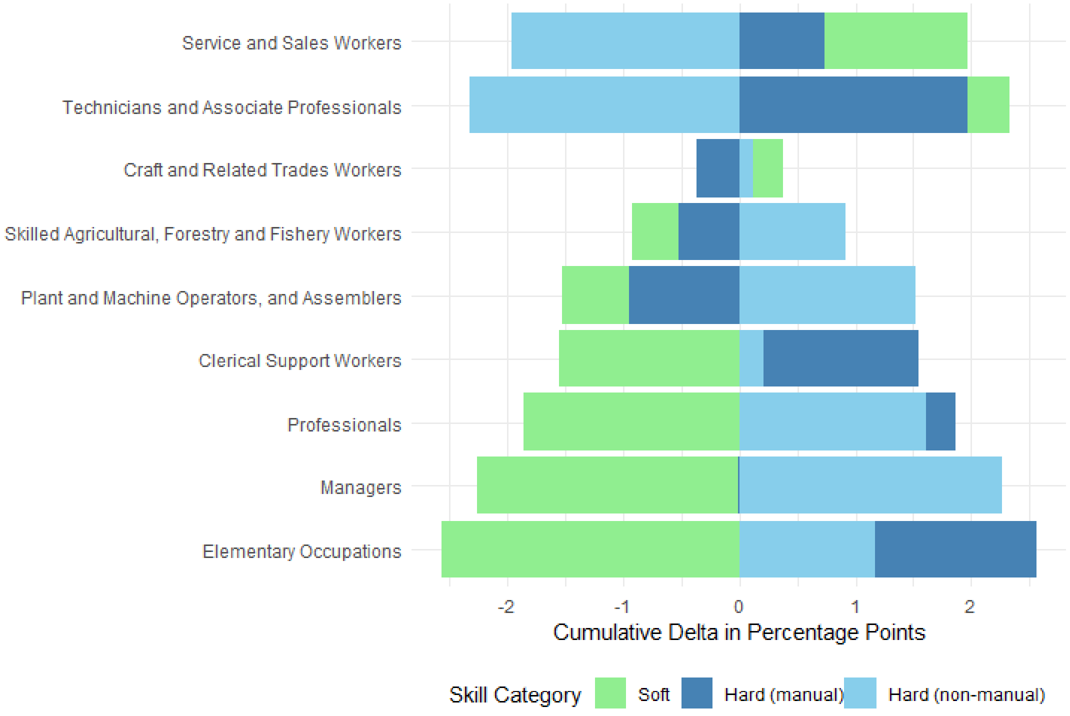
For my analysis on Switzerland, I do not have access to census data; instead, I utilize a publicly available, representative data set of job market postings. This data set is collected annually by the Swiss Job Market Monitor (SJMM), which is part of the Institute of Sociology at the University of Zurich (Buchmann et al., 2024). During a one-week sampling period in March, job postings are gathered from major job portals, company websites, and, until 2019, print media. The data set extends back to 1950, but to align with my analysis for the US, I focus on the period from 2013 onwards. Here, however, I can also include data for the most recent year, 2023. I supplement the data on job postings with information from the Swiss Federal Statistical Office to calculate several control variables for use in the regression analysis. I describe this procedure more in detail in the methodology section. Although a direct comparison with the US data set is difficult in several respects, it might be worth noting that the Swiss data set is considerably smaller. While the US Census data contain over 3 million data points each year, which can be scaled to represent the entire population using person weights, the Swiss data set only includes about 4,000 job postings annually.

In theory, the Swiss data set enables a very detailed analysis of specific job postings, as they are provided in text form. However, I have chosen not to utilize this information. Instead, I use a summarized data set that contains the occupational ISCO code for each job posting. I thus proceed in a very similar way as with the US data and map the skill intensities to the job postings based on occupational codes. The ISCO codes are again different from the ones used in the US Census, which requires me to create another mapping from O*NET to ISCO codes and to calculate the skill intensities for this set of

Table 3: **Development of Swiss Skill Intensities and AI-Related Job Postings**

Year	**Soft**	**Hard (manual)**	**Hard (non-manual)**	**AI-related Job Postings**
2023	50.3%	21.7%	28.0%	237
2022	51.5%	20.0%	28.5%	289
2021	50.2%	22.1%	27.8%	272
2020	50.8%	22.7%	26.6%	276
2019	50.7%	22.5%	26.8%	261
2018	49.7%	22.7%	27.6%	224
2017	49.3%	24.2%	26.5%	182
2016	50.5%	21.8%	27.7%	145
2015	49.3%	24.0%	26.8%	154
2014	49.2%	23.3%	27.5%	149
2013	50.5%	22.1%	27.3%	152

Figure 3: **Cumulative Delta of Swiss Skill Intensities by Occupational Group 2013-2023**



occupations. A potential concern with this procedure is that the O*NET task descriptions specifically refer to occupations in the US, and may not be directly comparable to other countries, such as Switzerland. While this is a valid point, I believe that the occupational differences are too minor to significantly impact the overall results. Nonetheless, I cannot entirely rule out this possibility.

The development of skill intensities resulting from yearly aggregation is presented in Table 3. A first interesting observation is that the general level of skill intensities seems to be comparable between the US and Switzerland. The soft skill intensity of an average worker similarly is around 50%, and also the shares between hard (manual) and hard (non-manual) are in a comparable range. There is a small tendency towards more non-manual and less manual hard skill tasks in Switzerland compared to the US. However different, there is no clear trend in the development of the skill intensities. The cumulative delta across all categories over the entire time period is close to zero, despite some fluctuations throughout the observation period. The occupational breakdown in Figure 3 supports this observation.[1] The chart shows that the cumulative deltas are much smaller and point, if anything, slightly to the opposite direction compared to the US. Clerical support workers and professionals, for instance, even seem to have experienced a slight decrease in their soft skill intensity.

Table 3 also includes the number of AI-related job postings in every year. Here, the general trend of increasing AI-related job postings is clearly visible, despite a significant decrease in the most recent year 2023. But due to the unclear trend in the skill intensities, this descriptive evidence already indicates that it might be difficult to find a strong relationship between the number of AI-related job postings and the skill intensities in the following regression analysis.

5 Methodology

I now want to investigate more formally whether, and to what extent, the increasing adoption of AI has already had an impact on the skill intensities in the US and Switzerland. To perform this analysis, I need, in addition to the skill intensities, a measure of AI adoption by firms. Since there is little data on actual AI adoption by firms yet, I use the number of people that work in AI-related occupations as a proxy, following Bonfiglioli et al. (2024). A key advantage of this approach is that it does not require any additional data sources, since I can derive the number of workers in AI-related occupations from the US Census and similarly the number of AI-related job market postings from the Swiss data directly. It also ensures that I have sufficient data over the past few years available to perform a robust analysis. However, a key drawback is that the number of AI-related jobs is arguably not the most direct measure of AI adoption. This implies that the results will likely not only capture AI adoption itself, but also broader technological developments. The list of occupations that I regard as AI-related in my analysis is presented in Table 4. For the US, this is the same set of occupations as in Bonfiglioli et al. (2024).

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[1] I do a breakdown by occupation instead of industry here, because I was not able to aggregate by industry for the Swiss data. Although the data set provides NOGA industry codes, they represent a simiplified version of the official nomenclature, and I was not able to find a mapping between the two.

Table 4: **AI-Related Occupations in US Census and Swiss Job Postings Data**

US Census Data (2018-2022)	
SOC Code	**SOC Title**
151211	Computer Systems Analysts
151221	Computer And Information Research Scientists
151230	Computer Support Specialists
151241	Computer Network Architects
151244	Network And Computer Systems Administrators
15124X	Database Administrators And Architects
151251	Computer Programmers
151252	Software Developers
151253	Software Quality Assurance Analysts And Testers
151254	Web Developers
151255	Web And Digital Interface Designers
151299	Computer Occupations, All Other
152031	Operations Research Analysts
1520XX	Other Mathematical Science Occupations
439111	Statistical Assistants

Swiss Job Postings Data	
ISCO Code	**ISCO Title**
2120	Mathematicians, Actuaries And Statisticians
2511	Systems Analysts
2512	Software Developers
2513	Web And Multimedia Developers
2514	Applications Programmers
2519	Software And Applications Developers And Analysts, Not Elsewhere Classified
2521	Database Designers And Administrators
2522	Systems Administrators
2523	Computer Network Professionals
2529	Database And Network Professionals, Not Elsewhere Classified
3314	Statistical, Mathematical And Related Associate Professionals
3512	Information And Communications Technology User Support Technicians
3513	Computer Network And Systems Technicians
3514	Web Technicians

Note: US occupational codes and titles were slightly different in the time period before 2018, which is why I only present the time period 2018-2022 here.

With regard to the level of observation, I aggregate the data at the year-region level for my main analysis. This is, for each year-region combination, I calculate the number of AI-related jobs as well as the average skill intensities before I proceed with the regression analysis. Important to note is that I exclude AI-related occupations in the aggregation of skill intensities in order to not have them included in both the dependent and independent variable. My region level for the US is the Place-of-Work Public Use Microdata Area (PWPUMA) which divides the US into about 1,000 regions. Unfortunately, this field is not always filled in the census data. I therefore use the Public Use Microdata Area (PUMA), which captures the location of people's home rather than their workplace, in cases where PWPUMA is not available. The PUMA regions are more granular then the PWPUMA, however I aggregate them to the level of PWPUMA to be consistent. I exclude data points where both PWPUMA and PUMA are not available.

Similarly for Switzerland, I aggregate at the year-region level, where regions are labor market areas. In total, there are 101 labor market areas in Switzerland. Again, I face the problem of missing entries. From a total of 43,280 individual job postings over the 11-year time horizon, the labor market area is missing in 5,799 cases. This is a relatively large fraction. However, a crosscheck of the occupational distribution between the data points with and without information on the labor market area shows that the distribution is very similar, differing by only a few percentage points. Therefore, I also exclude these data points from further analysis.

So far, I have aggregated the skill intensities as well as the number of AI-related jobs/ job market postings to the year-region level. I add several control variables to this data set that I believe could have an impact on the skill intensities. They are intended to capture, at least in parts, education, industry, employment, gender and age structure. For instance with regard to education, it is very likely that more educated workers perform more soft skill-intensive tasks, independent of the number of AI-related jobs in that region. Alternatively, with regard to industry structure, a large share of manufacturing may be associated with lower soft skill intensity, again independent of the number of AI-related jobs. Employment, gender and age structure could similarly impact the skill intensities. For the US, I obtain the information on the control variables directly from the census data set. For Switzerland, I use data from the Swiss Federal Statistical Office. Specifically, I calculate the following five control variables:

- **percentage_college**: For the US, the share of people between 25 and 65 with at least one year of college (education codes 07-11). For Switzerland, the share of people between 25 and 64 with a tertiary degree.
- **percentage_ind_manufacturing**: For the US, the share of employed people that work in the manufacturing sector (industry codes 1070-3990). For Switzerland, the share of workplaces in the secondary sector.
- **percentage_unemployed**: For the US, the share of the labor force that is unemployed. For Switzerland, the unemployment rate reported by the Swiss State Secretariat for Economic Affairs (SECO).
- **percentage_female_employment**: For the US, the share of females between 20 and 65 that are employed. For Switzerland the share of females between 20 and 64 that are employed.

- **percentage_over65**: For both countries, the share of people with age 65 or above.

All control variables are calculated at the year-region level. Regarding the Swiss control variables, the data at the level of the labor market area are only available for the years 2016-2022 for percentage_unemployed and percentage_over65 and for the years 2016-2021 for percentage_college, percentage_ind_manufacturing, and percentage_female_employment. For missing years, I use data from the nearest available year.

With all data being aggregated and prepared, I run the following regressions:

$$\text{Soft}_{r,t} = \alpha_{\text{S}} + \beta_{\text{S}} \cdot \text{AI\_Jobs}_{r,t} + X'_{r,t}\gamma_{\text{S}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{S}}_{r,t} \tag{16}$$

$$\text{Hard\_manual}_{r,t} = \alpha_{\text{H,M}} + \beta_{\text{H,M}} \cdot \text{AI\_Jobs}_{r,t} + X'_{r,t}\gamma_{\text{H,M}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{H,M}}_{r,t} \tag{17}$$

$$\text{Hard\_non\_manual}_{r,t} = \alpha_{\text{H,N}} + \beta_{\text{H,N}} \cdot \text{AI\_Jobs}_{r,t} + X'_{r,t}\gamma_{\text{H,N}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{H,N}}_{r,t} \tag{18}$$

In these equations, $\text{Soft}_{r,t}$, $\text{Hard\_manual}_{r,t}$ and $\text{Hard\_non\_manual}_{r,t}$ refer to the skill intensities in region r and year t, $\text{AI\_Jobs}_{r,t}$ is the number of AI-related jobs/ job postings in region r and year t, and $X_{r,t}$ is the vector of control variables, as described before. The subscripts to the coefficients refer to the skill categories: S for soft, H,M for hard (manual) and H,N for hard (non-manual). In addition, all models include time (δ_t) and region ($\lambda_{R(r)}$) fixed effects. With regard to region fixed effects, it should be noted that I do not apply them at the level of the labor market area, but at a higher level, denoted by $R(r)$. For the US, this is the state level; for Switzerland, this is the level of large labor market areas, of which there are 16. The rationale behind it is that I do not want to take out too much variation by applying fixed effects to a relatively small area.

An important question is whether the estimates of the OLS regression can be regarded as causal. The inclusion of several different control variables certainly mitigates concerns about omitted variable bias, however they might not fully remove them. For instance, there may be cofounders that are hard to measure such as cultural attitudes towards innovation or historical economic development patterns. These could influence both the number of AI-related jobs as well as the skill intensities. In addition, reverse causality might be an issue. It could potentially be that regions with a high level of soft skill intensity attract more AI-related jobs, for instance because companies value those complementary skills in their workforce.

To be more certain that my estimates can indeed be regarded as causal, I proceed with an Instrumental Variable (IV) approach and use proximity from each labor market area to universities that are strong in AI-related research as an instrument for AI-related jobs. More specifically, I extract the universities that are strong in AI-related research from the QS World University Ranking 2024, subject Computer Science and Information Systems. This ranking is not specifically on AI, however I believe it is reasonable to assume that universities that are ranked highly in computer science more generally are also strong in AI-related research. For the US, I consider universities up to rank 200, in total 43 universities. For Switzerland, due to the overall lower amount of universities, I consider all universities in the ranking, in total 9. I then calculate the adjusted distance between all labor market areas and all universities, whereby the adjusted distance is the distance in kilometers divided by a weight between zero and one that reflects the position of the university in the ranking. This is, if two universities are equally far away from a labor market area in terms of actual distance in kilometers, the higher ranked university would be closer in terms of adjusted distance. To perform these calculations, I rely on the tool ArcGIS. I choose the university with the smallest adjusted distance and add this information to the data set.

The idea for this instrument comes from Babina et al. (2024) who similarly use "firms' ex-ante exposure to the supply of AI talent from universities that are historically strong in AI research" (p. 14). However, this paper does not use proximity directly, but a more complex measure that has ex-ante strength of an university in AI research as well as the degree of firm-university hiring networks as inputs. Compared to my approach, theirs makes a greater effort to identify universities that were historically strong in AI research, and not computer science more broadly. Another difference is that their analysis is conducted at the firm level, which is why their instrument differs in that respect.

Proximity to AI-strong universities likely fulfills the relevance criterion for an IV, as AI-related jobs are often concentrated near tech universities. An example would be Silicon Valley and Stanford University in the US. This is also supported by the results of the first stage regression which I present in the results section. The exogeneity criterion seems to be satisfied, too, as it is unlikely that the proximity to universities influences the skill intensities directly. Rather, the influence is through the types of jobs that these universities attract, for instance AI-related jobs. However, since exogeneity cannot be tested empirically, I also rely on the fact that a similar instrument has been used in the literature before.

I run the first stage regression of the IV as follows:

$$\text{AI\_Jobs}_{r,t} = \alpha + \beta \cdot \text{ADJ\_DIST}_r + X'_{r,t}\gamma + \delta_t + \lambda_{R(r)} + \epsilon_{r,t}, \tag{19}$$

where ADJ_DIST_r refers to the smallest adjusted distance of labor market area r to an AI-strong university. All other variables are as before. Note that the adjusted distance is time-invariant. In this respect, it is also advantageous that I do not use fixed effects at the level of the labor market area directly, but at a higher regional level, so that the fixed effects do not absorb too much of the time-invariant IV. The second stage regressions look almost the same as the OLS regressions from above. The only change is that the number of AI-related jobs is now replaced by the estimate from the first stage regression:

$$\text{Soft}_{r,t} = \alpha_{\text{S}} + \beta_{\text{S}} \cdot \widehat{\text{AI\_Jobs}}_{r,t} + X'_{r,t}\gamma_{\text{S}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{S}}_{r,t} \tag{20}$$

$$\text{Hard\_manual}_{r,t} = \alpha_{\text{H,M}} + \beta_{\text{H,M}} \cdot \widehat{\text{AI\_Jobs}}_{r,t} + X'_{r,t}\gamma_{\text{H,M}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{H,M}}_{r,t} \tag{21}$$

$$\text{Hard\_non\_manual}_{r,t} = \alpha_{\text{H,N}} + \beta_{\text{H,N}} \cdot \widehat{\text{AI\_Jobs}}_{r,t} + X'_{r,t}\gamma_{\text{H,N}} + \delta_t + \lambda_{R(r)} + \epsilon^{\text{H,N}}_{r,t} \tag{22}$$

One take-away from the descriptive evidence in section 4 was that some industries experienced a particularly strong increase in their soft skill intensity throughout the observation period, while others did not. This was especially the case in the US, and less so in Switzerland. So far, my regression analysis has not differentiated between industries. I thus run an additional configuration specifically for the US with the goal to find out whether these differential changes for different industries can be related to the number of AI-related jobs. To do this, I introduce a third layer to my data set, making the adjusted level of observation year-region-industry, and run the following regressions:

$$\text{Soft}_{r,t,i} = \alpha_{\text{S}} + \beta_1^{\text{S}} \cdot \text{AI\_Jobs}_{r,t,i} + \beta_2^{\text{S}} \left(\text{AI\_Jobs}_{r,t,i} \times \text{IND\_group}\right) + \delta_t + \lambda_{R(r)} + \epsilon_{r,t,i}^{\text{S}} \tag{23}$$

$$\text{Hard\_manual}_{r,t,i} = \alpha_{\text{H,M}} + \beta_1^{\text{H,M}} \cdot \text{AI\_Jobs}_{r,t,i} + \beta_2^{\text{H,M}} \left(\text{AI\_Jobs}_{r,t,i} \times \text{IND\_group}\right) + \delta_t + \lambda_{R(r)} + \epsilon_{r,t,i}^{\text{H,M}} \tag{24}$$

$$\text{Hard\_non\_manual}_{r,t,i} = \alpha_{\text{H,N}} + \beta_1^{\text{H,N}} \cdot \text{AI\_Jobs}_{r,t,i} + \beta_2^{\text{H,N}} \left(\text{AI\_Jobs}_{r,t,i} \times \text{IND\_group}\right) + \delta_t + \lambda_{R(r)} + \epsilon_{r,t,i}^{\text{H,N}} \tag{25}$$

In this configuration, the skill intensities as well as the number of AI-related jobs are aggregated at the region(r)-year(t)-industry(i) level. In addition to the variable $\text{AI\_Jobs}_{r,t,i}$, I include the interaction term $\text{AI\_Jobs}_{r,t,i} \times \text{IND\_group}$ here to be able to analyze the effect of the number of AI-related jobs on the skill intensities for different industries. In contrast to the previous configurations, I do not include any control variables, but keep time as well as higher-level regional fixed effects.

6 Results

6.1 US

The results of the OLS regressions from equations (16)–(18) for the US are presented in Table 5. For the regressions of soft skill intensity on AI-related jobs, the control variables were added step-by-step (columns 1–5). For the regressions of manual and non-manual hard skill intensity on AI-related jobs, only two configurations are reported: one without any controls (columns 6 and 8) and one with all controls (columns 7 and 9). Note that the number of AI-related jobs in the variable AI_Jobs_10000 is scaled by the factor of 10,000, such that the coefficients have to be interpreted as the change in the skill intensity in percentage points for 10,000 additional AI-related jobs. As briefly mentioned before, the total number of observations represents the number of Place-of-Work PUMAs over the period of ten years: 982 for the years between 2013 and 2021 and 1,004 for the year 2022, in total 9,842.

Table 5: **US OLS**

	Dependent variable:								
	[——soft——				]	[——hard_manual——	]	[—hard_non_manual—	]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI_Jobs_10000	1.133***	0.258***	0.289***	0.297***	0.308***	−1.213***	−0.320***	0.080***	0.012
	(0.136)	(0.033)	(0.030)	(0.031)	(0.032)	(0.147)	(0.035)	(0.017)	(0.014)
percentage_college		0.346***	0.318***	0.332***	0.335***		−0.350***		0.015***
		(0.005)	(0.005)	(0.006)	(0.006)		(0.007)		(0.003)
percentage_ind_manufacturing			−0.120***	−0.116***	−0.116***		0.151***		−0.035***
			(0.007)	(0.007)	(0.007)		(0.008)		(0.003)
percentage_unemployed				−0.0003	0.005		−0.001		−0.005
				(0.014)	(0.014)		(0.015)		(0.007)
percentage_female_employment				−0.027***	−0.022***		0.013		0.009***
				(0.007)	(0.007)		(0.008)		(0.003)
percentage_over65					0.026**		−0.022*		−0.004
					(0.010)		(0.012)		(0.006)
Observations	9,842	9,842	9,842	9,842	9,842	9,842	9,842	9,842	9,842
R^2	0.403	0.824	0.844	0.844	0.845	0.371	0.832	0.156	0.228
Adjusted R^2	0.399	0.823	0.843	0.843	0.844	0.367	0.831	0.151	0.223

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All configurations include year and state fixed effects. Standard errors are clustered at the Place-of-Work PUMA level.

In line with expectations, the relation between AI-related jobs and the soft skill intensity is positive and significant. In the configuration with all control variables (column 5), 10,000 additional AI-related jobs are associated with an increase in the soft skill intensity by 0.308 percentage points. The effect size is stable for almost all configurations, only the first without any controls shows a higher effect. I would interpret this effect size as moderately high. Since the observation level is year-region, it can also be interpreted as follows: if one region has 10,000 more AI-related jobs than another in a given year, their soft skill intensity is on average 0.308 percentage points higher. This seems neither gigantically large, nor unimportantly small. However different from what was expected, this increase is fully counterbalanced by a decrease in the manual, and not the non-manual, hard skill intensity. It is worth noting again that, due to my methodology, all three coefficients for the same configuration have to sum up to zero. Specifically, the coefficients for AI_Jobs_10000 in columns 1, 6, and 8 as well as those in columns 5, 7, and 9 have to be zero in total. In the configuration with all control variables (column 7), 10,000 additional AI-related jobs are associated with a decrease in the manual hard skill intensity by 0.32 percentage points. This is surprising because the prediction was that the manual hard skill intensity could even increase with more AI-related jobs. In contrast, the coefficient for AI_Jobs_10000 in the non-manual hard skill regression (column 9), which was expected to be negative, is close to zero and insignificant. I will discuss potential reasons for this pattern together with the IV and industry results later.

It is also interesting to take a brief look at the signs and magnitudes of the control varibles. Significantly positively related to the soft skill intensity is the percentage of people who attended college. This matches expectations, as it seems intuitive that workers with more education take over more soft skill-intensive tasks, such as management. Although the coefficient is in a similar range to that for AI-related jobs, a direct comparison is difficult due to different units: the coefficients for the control variables reflect the effect of a one-percentage-point increase, not a one-unit increase. In addition, the percentage of people who work in the manufacturing industry is negatively related to the soft skill intensity. This also seems reasonable, as manual tasks often require less soft skills. The coefficients for the other three control variables are much smaller and less significant, suggesting that they do not significantly impact skill intensities.

Turning to the IV regressions, Table 6 presents the results of the first stage regression from equation (19). As expected, the coefficient on ADJ_DIST, the adjusted distance between a labor market area and the closest AI-strong university, is negative. That is, the farther a labor market region is from an AI-strong university, the fewer AI-related jobs there are. In the configuration with all controls (column 5), an increase in the adjusted distance by one kilometer is associated with a reduction in the number of AI-related jobs by 11.44. The effect size is very similar throughout all configurations. I would consider this as a relatively large effect, especially in comparison with the Swiss data, as we will see later. The instrument also passes the IV relevance criterion with an F-value of approximately 17. It is important to note that this value was calculated with standard errors clustered at the Place-of-Work PUMA level, as in all regressions for the US. Without clustering, the F-value is much higher than that.

Using the prediction for AI-related jobs from the first stage, I run the second stage regression from equations (20)–(22). The results are shown in Table 7. They strongly support

Table 6: **US IV First Stage**

	Dependent variable:				
	AI_Jobs				
	(1)	(2)	(3)	(4)	(5)
ADJ_DIST	-11.98^{***}	-11.37^{***}	-10.88^{***}	-11.55^{***}	-11.44^{***}
	(3.17)	(2.82)	(2.76)	(2.83)	(2.78)
percentage_college		620.58^{***}	651.02^{***}	539.92^{***}	457.65^{***}
		(61.46)	(69.02)	(69.82)	(68.50)
percentage_ind_manufacturing			142.16^{*}	119.07	109.79
			(75.09)	(77.20)	(76.90)
percentage_unemployed				254.84^{***}	102.94
				(93.09)	(91.74)
percentage_female_employment				261.39^{***}	143.55^{**}
				(68.90)	(63.67)
percentage_over65					-643.89^{***}
					(95.77)
Observations	9,842	9,842	9,842	9,842	9,842
R^2	0.12	0.26	0.26	0.27	0.29
Adjusted R^2	0.12	0.26	0.26	0.26	0.29

Note: *p<0.1; **p<0.05; ***p<0.01

All configurations include year and state fixed effects. Standard errors are clustered at the Place-of-Work PUMA level.

the OLS results: the coefficients for AI-related jobs are positive and significant in the soft skill regressions, negative and significant in the manual hard skill regressions, and zero and insignificant in the non-manual hard skill regressions. However, the effect size is much larger. According to the second stage IV results, 10,000 additional AI-related jobs are associated with an increase in the soft skill intensity by 1.258 percentage points (column 5) and a decrease in the manual hard skill intensity by 1.211 percentage points (column 7). These values are four times higher than in the OLS regression, indicating that the true effect is larger than estimated by OLS. On the other hand, the standard errors are higher in the second stage IV which cautions against overinterpreting the point estimates. The coefficients for the control variables are similar to those in the OLS.

As previously mentioned, these results raise the question of why the increase in the soft skill intensity is counterbalanced by a decrease in the manual, and not the non-manual hard skill intensity. A starting point to investigate this might be a closer look back at Table 2 and Figure 2. The descriptive evidence already showed that the increases in the soft skill intensity were largely offset by decreases in the manual hard skill intensity. The reductions in the non-manual hard skill intensity were relatively small, leaving less room for AI-related jobs to explain these smaller effects.

A first potential factor explaining why this is the case could be related to my methodol-

Table 7: **US IV Second Stage**

	Dependent variable:								
	[——soft——]					[——hard_manual——]		[—hard_non_manual—]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI_Jobs_10000	1.204^{*}	0.955^{**}	1.379^{***}	1.244^{***}	1.258^{***}	−1.059	-1.211^{***}	−0.145	−0.047
	(0.631)	(0.375)	(0.418)	(0.338)	(0.366)	(0.703)	(0.451)	(0.142)	(0.133)
percentage_college		0.303^{***}	0.247^{***}	0.279^{***}	0.289^{***}		-0.307^{***}		0.018^{**}
		(0.026)	(0.028)	(0.020)	(0.019)		(0.024)		(0.008)
percentage_ind_manufacturing			-0.139^{***}	-0.130^{***}	-0.129^{***}		0.163^{***}		-0.034^{***}
			(0.012)	(0.011)	(0.011)		(0.012)		(0.005)
percentage_unemployed				−0.025	−0.005		0.009		−0.004
				(0.019)	(0.019)		(0.018)		(0.007)
percentage_female_employment				-0.049^{***}	-0.034^{**}		0.023		0.010^{**}
				(0.016)	(0.015)		(0.016)		(0.004)
percentage_over65					0.087^{***}		-0.080^{**}		−0.008
					(0.026)		(0.033)		(0.011)
Observations	9,842	9,842	9,842	9,842	9,842	9,842	9,842	9,842	9,842
R^2	0.402	0.782	0.741	0.767	0.770	0.369	0.774	0.071	0.223
Adjusted R^2	0.398	0.781	0.739	0.766	0.768	0.365	0.772	0.065	0.218

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All configurations include year and state fixed effects. Standard errors are clustered at the Place-of-Work PUMA level.

ogy. Remember that the classification of tasks and occupations is based on action verbs. For soft skills, I had a clear definition from O*NET which helped me in the classification process. I am therefore most confident with regard to the classification of soft skill verbs which is supported by the high correlation of the soft skill intensities with the O*NET importance scores, as outlined in section 4. For the remaining verbs, I had to decide whether I categorize them as manual or non-manual largely based on my personal reasoning. To give an example, I categorized the verb "operate" as manual. However, while "operate" can indeed describe a manual activity which is difficult to substitute by technology, it could also describe an activity which is easily automatable, for instance simply pressing a button. The regression results are very strong, so it is unlikely that the classification methodology alone explains the observed pattern. I just want to caution that my methodology is a bit less certain about the differentiation between manual and non-manual hard skill verbs compared to soft skill verbs.

A second methodology-related explanation could be the fact that I proxy AI adoption by the number of AI-related jobs, where AI-related jobs include a range of jobs in the IT sector. As briefly described before, I thus do not only capture AI-related developments, but very likely also broader technical advancements. For instance, if software developers automate production processes that were previously performed manually by humans, this would be included in my analysis. This potentially explains why I find a very strong negative, and even causal, relationship between the number of AI-related jobs and the manual hard skill intensity. A final explanation could be related to the time period I investigate. Since my data for the US ends in 2022, it might simply be too early to see the expected effects of AI in the non-manual hard skill intensity, for instance with respect to office positions.

To shed further light to the results, I additionally perform a breakdown by industry. Table 8 presents the results of the regressions from equations (23)–(25). Different from before, the number of AI-related jobs is only scaled by the factor of 1,000 here. This reflects the fact that the effects are larger on a more granular level of observation. Compared to the previous regressions, the total number of observations has increased by a factor of 14, the number of industries. The results table is structured as follows: the first line AI_Jobs_1000 represents the effect of 1,000 additional AI-related jobs on the skill intensities in the agriculture industry, the base industry. The following 13 lines show the coefficients for the industry dummies relative to the agriculture industry. For instance, working in the education industry instead of the agriculture industry increases the average soft skill intensity by 25.623 percentage points. Finally, there are 13 interaction terms of AI-related jobs and the industry dummies.

To receive the effect of AI-related jobs on the skill intensities for a specific industry, the coefficient for AI_Jobs_1000 and the interaction term for this industry have to be summed up. For instance with regard to the manufacturing industry, 1,000 additional AI-related jobs are associated with an increase in the soft skill intensity by 1.865 (=4.410–2.545) percentage points and a decrease in the manual hard skill intensity by 2.189 (=–5.694+3.505) percentage points. The manufacturing industry is indeed one of the industries with the largest overall effects. Although this might be surprising, it supports the previous argument that AI-related occupations, as I classify them, might have contributed more to the substitution of manual, and less to the substitution of non-manual tasks so far.

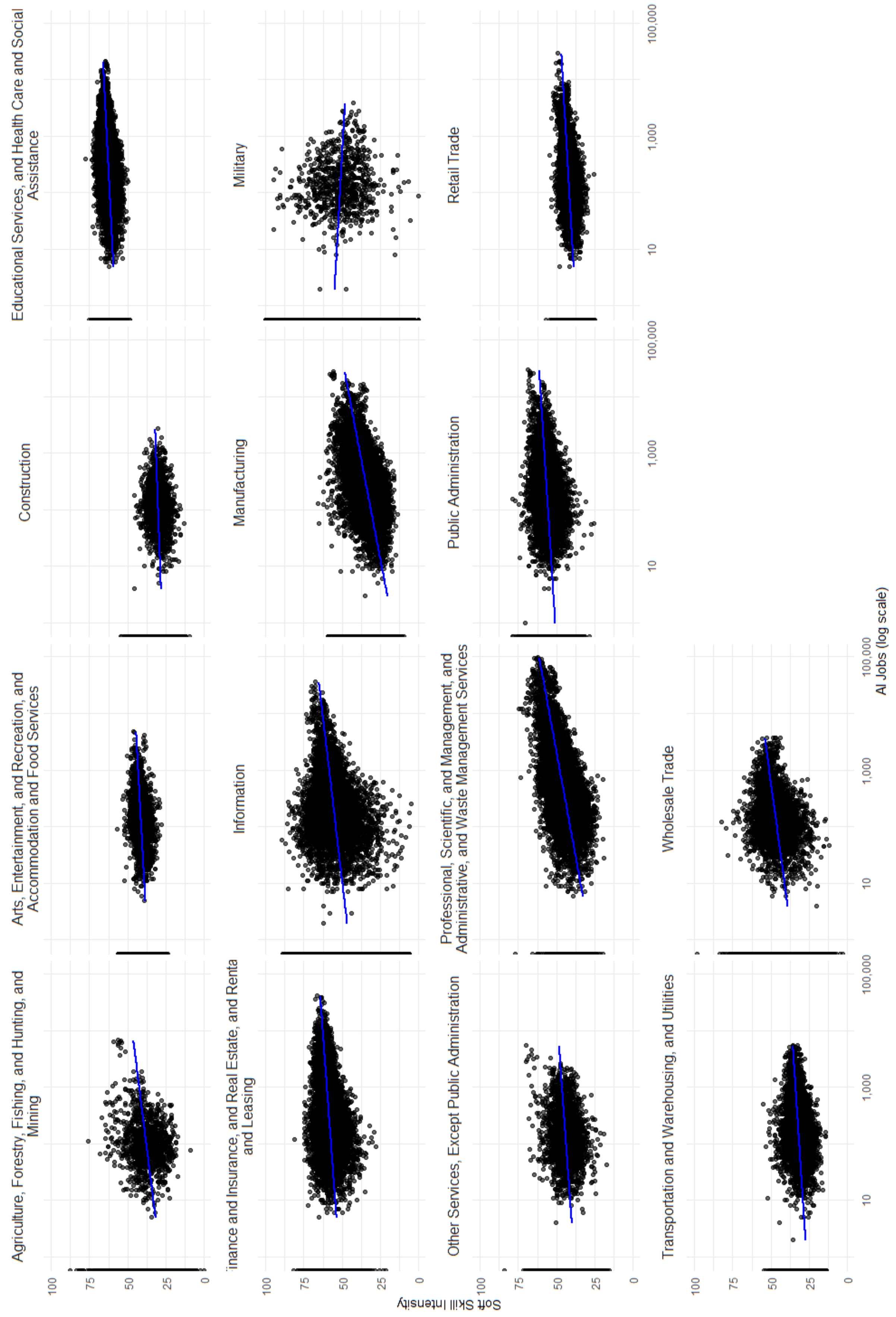
Table 8: **US OLS by Industrial Group**

	Dependent variable:		
	soft	hard_manual	hard_non_manual
	(1)	(2)	(3)
AI_Jobs_1000	4.410^{***}	-5.694^{***}	1.285^{***}
	(0.897)	(1.311)	(0.426)
IND_groupArts, Entertainment, and Recreation, and Accommodation and Food Services	2.699^{***}	-5.075^{***}	2.376^{***}
	(0.163)	(0.209)	(0.073)
IND_groupConstruction	-8.224^{***}	13.160^{***}	-4.936^{***}
	(0.165)	(0.213)	(0.070)
IND_groupEducational Services, and Health Care and Social Assistance	25.623^{***}	-24.783^{***}	-0.839^{***}
	(0.171)	(0.214)	(0.071)
IND_groupFinance and Insurance, and Real Estate, and Rental and Leasing	20.478^{***}	-35.133^{***}	14.655^{***}
	(0.184)	(0.196)	(0.099)
IND_groupInformation	17.155^{***}	-23.567^{***}	6.412^{***}
	(0.224)	(0.240)	(0.096)
IND_groupManufacturing	-4.578^{***}	4.351^{***}	0.227^{***}
	(0.256)	(0.316)	(0.081)
IND_groupMilitary	17.050^{***}	-18.801^{***}	1.751^{***}
	(0.386)	(0.382)	(0.176)
IND_groupOther Services, Except Public Administration	5.559^{***}	-2.526^{***}	-3.032^{***}
	(0.174)	(0.212)	(0.073)
IND_groupProfessional, Scientific, and Management, and Administrative, and Waste Management Services	8.444^{***}	-14.011^{***}	5.567^{***}
	(0.218)	(0.251)	(0.077)
IND_groupPublic Administration	19.125^{***}	-26.829^{***}	7.704^{***}
	(0.174)	(0.210)	(0.080)
IND_groupRetail Trade	4.718^{***}	-17.229^{***}	12.511^{***}
	(0.169)	(0.212)	(0.070)
IND_groupTransportation and Warehousing, and Utilities	-6.143^{***}	-3.472^{***}	9.615^{***}
	(0.181)	(0.216)	(0.075)
IND_groupWholesale Trade	7.431^{***}	-15.237^{***}	7.805^{***}
	(0.218)	(0.257)	(0.085)
AI_Jobs_1000:IND_groupArts, Entertainment, and Recreation, and Accommodation and Food Services	-1.285	2.475^{*}	-1.189^{***}
	(1.052)	(1.412)	(0.441)
AI_Jobs_1000:IND_groupConstruction	-0.004	0.081	-0.077
	(0.673)	(0.947)	(0.340)
AI_Jobs_1000:IND_groupEducational Services, and Health Care and Social Assistance	-3.947^{***}	5.116^{***}	-1.169^{***}
	(0.889)	(1.300)	(0.423)
AI_Jobs_1000:IND_groupFinance and Insurance, and Real Estate, and Rental and Leasing	-3.823^{***}	5.498^{***}	-1.675^{***}
	(0.901)	(1.308)	(0.432)
AI_Jobs_1000:IND_groupInformation	-3.304^{***}	4.814^{***}	-1.510^{***}
	(0.904)	(1.310)	(0.429)
AI_Jobs_1000:IND_groupManufacturing	-2.545^{***}	3.505^{***}	-0.960^{**}
	(0.909)	(1.316)	(0.423)
AI_Jobs_1000:IND_groupMilitary	-10.894^{***}	10.838^{***}	0.056
	(1.488)	(1.744)	(0.635)
AI_Jobs_1000:IND_groupOther Services, Except Public Administration	-0.283	1.081	-0.799^{*}
	(0.934)	(1.317)	(0.429)
AI_Jobs_1000:IND_groupProfessional, Scientific, and Management, and Administrative, and Waste Management Services	-3.975^{***}	5.285^{***}	-1.310^{***}
	(0.891)	(1.305)	(0.426)
AI_Jobs_1000:IND_groupPublic Administration	-3.870^{***}	5.139^{***}	-1.269^{***}
	(0.914)	(1.326)	(0.430)
AI_Jobs_1000:IND_groupRetail Trade	-3.586^{***}	5.151^{***}	-1.565^{***}
	(0.901)	(1.308)	(0.431)
AI_Jobs_1000:IND_groupTransportation and Warehousing, and Utilities	-2.235^{***}	4.036^{***}	-1.800^{***}
	(0.836)	(1.285)	(0.480)
AI_Jobs_1000:IND_groupWholesale Trade	1.456	-0.691	-0.765^{*}
	(0.944)	(1.258)	(0.416)
Observations	133,653	133,653	133,653
R^2	0.609	0.696	0.616
Adjusted R^2	0.609	0.696	0.615

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All configurations include year and state fixed effects. Standard errors are clustered at the Place-of-Work PUMA level.

Figure 4: **Relationship between the Number of AI-Related Jobs and Soft Skill Intensity by Industrial Group in the US**



It is further interesing to take a look at the results for the finance industry. This was the industry with the highest cumulative increase in the soft skill intensity over the whole observation period (cf. Figure 2). In connection with AI-related jobs, the increase in the soft skill intensity is less strong than for the manufacturing industry (+0.589 percentage points for 1,000 additional AI-related jobs). However, this increase is largely counterbalanced by a decrease in the non-manual hard skill intensity (–0.391 percentage points for 1,000 additional AI-related jobs), in line with the initial predictions. But this industry is an exception. For most industries, the increase in the soft skill intensity is offset by a decrease in the manual hard skill intensity.

Figure 4 provides a clearer view of which industries exhibit the strongest relationship between the number of AI-related jobs and the soft skill intensity. Note that the number of AI-related jobs is on a log-scale here. The charts show very well that the number of AI-related jobs is positively related to the soft skill intensity in almost all industries, and that the relationship is particularly strong in the manufacturing industry.

6.2 Switzerland

Compared to the US, the Swiss results are unfortunately much less robust. Table 9 shows the results of the OLS regressions from equations (16)–(18) for Switzerland. The structure of the table is the same as for the US: for the soft skill regressions the control variables were added step-by-step, while for the hard skill regressions, only two configurations are reported. However, a notable difference is that the variable AI_Jobs is not scaled by any factor here. The results thus have to be interpreted as the change in the skill intensities in percentage points per one additional AI-related job posting. One could think that this is due to the fact that the impact of AI-related jobs is much stronger in Switzerland, however this is certainly not the case. The reason for this, rather, is the much thinner data base. Table 3 already showed that the number of AI-related job postings in Switzerland is in the range of 200 per year. In contrast, the US data (after applying the person weights) contain several millions of AI-related jobs. The different scales are thus not surprising, but at the same time make a direct comparison between the US and Swiss results impossible. A brief note on the number of observations: since the observation level is year-region again, it should theoretically correspond to the number of labor market areas multiplied by the number of years (101 × 11). However, for some regions and some years, there were no job postings recorded, such that the total number of observations is with 1,068 a little less.

The regression results show that only the coefficients without control variables are significant. As soon as controls are added, the significance disappears. But at least the sign is consistent throughout the configurations: the coefficients on AI_Jobs are positive in all soft skill regressions, negative in the manual hard skill regressions and again positive in the non-manual hard skill regressions. This is a small indication that AI-related job postings are more likely positively associated with the soft skill intensity and more likely negatively associated with the manual hard skill intensity, similar as what was shown for the US. Moreover, there is no sign of a decrease in the non-manual hard skill intensity

Table 9: **CH OLS**

	Dependent variable:								
	[——soft——]					[—hard_manual—]		[—hard_non_manual—]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI_Jobs	0.151***	0.074	0.037	0.035	0.032	−0.289***	−0.093	0.138***	0.061
	(0.051)	(0.048)	(0.050)	(0.051)	(0.047)	(0.077)	(0.066)	(0.043)	(0.040)
percentage_college		0.161**	−0.008	−0.009	−0.009		−0.003		0.012
		(0.069)	(0.108)	(0.106)	(0.106)		(0.114)		(0.066)
percentage_ind_manufacturing			−0.581***	−0.577**	−0.577**		0.682**		−0.105
			(0.216)	(0.231)	(0.233)		(0.273)		(0.136)
percentage_unemployed				0.094	0.090		−0.889		0.799**
				(0.768)	(0.775)		(0.916)		(0.346)
percentage_female_employment				0.023	0.021		−0.070		0.049
				(0.194)	(0.190)		(0.208)		(0.097)
percentage_over65					−0.031		0.363		−0.332***
					(0.291)		(0.333)		(0.129)
Observations	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068
R^2	0.085	0.091	0.099	0.099	0.099	0.136	0.159	0.093	0.107
Adjusted R^2	0.062	0.067	0.074	0.073	0.072	0.114	0.134	0.071	0.080

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All configurations include year and large labor market area fixed effects. Standard errors are clustered at the labor market area level.

Table 10: **CH IV First Stage**

	Dependent variable:				
	AI_Jobs				
	(1)	(2)	(3)	(4)	(5)
ADJ_DIST	-0.08^{***}	-0.04^{**}	-0.05^{***}	-0.04^{***}	-0.02
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
percentage_college		0.28	0.11	0.10	0.14
		(0.18)	(0.13)	(0.12)	(0.12)
percentage_ind_manufacturing			-0.51^{*}	-0.48^{*}	-0.41^{*}
			(0.28)	(0.26)	(0.24)
percentage_unemployed				1.05^{**}	1.04^{**}
				(0.48)	(0.46)
percentage_female_employment				0.08	0.03
				(0.09)	(0.07)
percentage_over65					-0.59
					(0.41)
Observations	1,068	1,068	1,068	1,068	1,068
R^2	0.20	0.29	0.32	0.33	0.36
Adjusted R^2	0.18	0.27	0.30	0.31	0.34

Note: *p<0.1; **p<0.05; ***p<0.01

All configurations include year and large labor market area fixed effects. Standard errors are clustered at the labor market area level.

with more AI-related job postings, rather a small indication of an increase. Maybe noteworthy is that the model fit, measured by R^2, is with about 0.1 quite weak. Thus, the explanatory power of AI-related job postings is overall very low.

Since there are far fewer data points in the Swiss job postings data compared to the US Census data, I check again in detail the underlying data and whether different configurations or adjustments to the data change the results. One observation with regard to the underlying data is that there are some year-region combinations where a lot of data points enter the aggregation, and others where very few do. For instance, for the Zurich labor market area, there are approximately 500 job market postings in every year, such that the aggregation arguably yields more or less representative results. For other regions, there are only one or two job postings per year that enter the aggregation. There is even one extreme case in the data, where the only job posting for a year-region combination is associated with a soft skill intensity of 100%. I thus wrongly assume that the average soft skill intensity for this year-region is 100%. To mitigate these effects, I try several modifications: the first is the exclusion of year-region combinations where only one or two observations enter. However, this adjustment does not have a major impact on the results. A second idea is to perform a weighted regression, where the weights are the number of observations that enter the aggregation. These results are slightly stronger, as presented in Table A1 in the appendix: now the coefficient on AI_Jobs, in the configura-

Table 11: **CH IV Second Stage**

	Dependent variable:					
	soft		hard_manual		hard_non_manual	
	(1)	(2)	(3)	(4)	(5)	(6)
AI_Jobs	0.070	−0.242	−0.308	0.145	0.238*	0.097
	(0.318)	(0.591)	(0.376)	(0.684)	(0.144)	(0.261)
percentage_college		0.035		−0.040		0.005
		(0.141)		(0.159)		(0.081)
percentage_ind_manufacturing		−0.690**		0.796**		−0.106
		(0.349)		(0.402)		(0.165)
percentage_unemployed		0.446		−1.278		0.832*
		(1.126)		(1.304)		(0.455)
percentage_female_employment		0.044		−0.114		0.070
		(0.179)		(0.204)		(0.099)
Observations	1,068	1,068	1,068	1,068	1,068	1,068
R^2	0.084	0.088	0.135	0.147	0.088	0.101
Adjusted R^2	0.061	0.061	0.114	0.123	0.065	0.075

Note: *p<0.1; **p<0.05; ***p<0.01

All configurations include year and large labor market area fixed effects. Standard errors are clustered at the labor market area level.

tion with all control variables, is significant at the 10% level in the soft skill and manual hard skill regressions. This provides some additional support for the initial observation that AI-related job postings are associated with an increase in the soft, and a decrease in the manual hard skill intensity. The coefficient on AI_Jobs in the non-manual hard skill regression remains insignificant, even after weighting.

In theory, it could be the case that the OLS results are weak because they do not reflect the true causal evidence. Although this seems very unlikely, I still proceed with the same procedure as for the US and use the smallest adjusted distance from a labor market area to an AI-strong university as an IV. The results of the first stage regression from equation (19) are reported in Table 10. Although the relationship is negative as expected, it is much weaker compared to the US. Here, an increase in the adjusted distance by one kilometer is associated with a decrease in the number of AI-related job postings by about 0.04 (column 4). Also the significance is less strong. For the configurations in columns 1, 3 and 4, the F-value is slightly below 10. For the other configurations, it is even weaker. For completeness, I run the second stage from equations (20)–(22) for the configurations in columns 1 and 4, where the F-value is at least close to 10, however being aware that the instrument is weak. It is thus not surprising that the second stage coefficients on AI_Jobs in Table 11 are insignificant. Besides the already weak initial relationship presented in the OLS, the instrument is likely too weak to provide meaningful additional insights.

Regarding the reasons for these results, I believe that a key explanation lies in the nature of the job postings data set. While the job postings are representative for Switzerland as a whole, they are not at the level of an individual labor market area. This makes the analysis much more difficult and less robust. In tendency, the OLS results support the observation from the US that the number of AI-related jobs is positively related to soft and negatively related to manual hard skill intensity. However, the relationship is weak, and most coefficients are insignificant. For a more direct comparison with the US, it would be helpful to repeat the analysis using Swiss census data.

7 Conclusion

To conclude, the analysis has shown that soft skills are in high and increasing demand in the labor market. According to my classification methodology, already now, about half of the tasks of an average worker in the US and Switzerland are soft skill-intensive. In particular in the US, there have been steady increases in the soft skill intensity over the past ten years. The main contribution of this thesis, however, lies in being among the first to connect changes in the soft and hard skill intensities to advances in technology, specifically AI adoption proxied by the number of AI-related jobs. With regard to the US, the results are highly significant and confirm the initial prediction that the number of AI-related jobs is positively related to the soft skill intensity, and negatively related to the hard skill intensity. This is further supported by the IV estimates, which give higher confidence that the relationship is indeed causal. However surprisingly, the increase in the soft skill intensity is counterbalanced by a decrease in the manual, and not the non-manual, hard skill intensity. This might in parts be explained by the fact that AI rollout has just begun, meaning that some effects may only become visible in the coming years. But beyond that, I cannot rule out that my proxy for AI adoption, AI-related jobs, captures broader technological advancements which are not immediately related to AI, for instance process automation in the manufacturing industry. As more direct measures of AI adoption become available, it would be interesting to see whether the results differ from mine and align more closely with the initial predictions when using such measures.

The results for Switzerland are less robust and less significant, but still tend to show a positive relationship between AI-related job postings and the soft skill intensity. However, the use of job market postings instead of census data makes it very difficult to directly compare the US and Swiss results. A key limitation is that the job market postings are much less representative at a more granular local level of observation, with sometimes only one or two, or even zero, observations. Swiss census data were not available for this study, but it would be useful to repeat the analysis using census data to more reliably compare the effect sizes between the US and Switzerland.

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Data Availability

All data and code are available in the folder "Data_Thesis_Pecksen.7z", uploaded on OLAT. This folder also includes a file, "Documentation.pdf", which explains the file structure and usage of the code.

Appendix

This appendix includes the derivations from the model section and an additional results table referenced in the main text. For the model, the production function was given as:

$$Y = [\alpha L_S^\rho + (1-\alpha) L_H^\rho]^{\frac{1}{\rho}}\,, \text{ where } L_H = L_{H,M}^\beta \left(L_{H,N} + \theta AI\right)^{1-\beta}.$$

1. $\mathbf{\frac{\partial Y}{\partial L_S}}$ **:**

$$\begin{aligned}
\frac{\partial Y}{\partial L_S} &= \frac{\partial}{\partial L_S}\left([\alpha L_S^\rho + (1-\alpha) L_H^\rho]^{\frac{1}{\rho}}\right) \\
&= \frac{1}{\rho}\left(\alpha L_S^\rho + (1-\alpha) L_H^\rho\right)^{\frac{1}{\rho}-1}\left(\alpha\rho L_S^{\rho-1}\right) \\
&= \alpha L_S^{\rho-1}\left(\alpha L_S^\rho + (1-\alpha) L_H^\rho\right)^{\frac{1}{\rho}-1} \\
&= \alpha Y^{1-\rho} L_S^{\rho-1}.
\end{aligned}$$

2. $\mathbf{\frac{\partial^2 Y}{\partial AI\,\partial L_S}}$:

$$\frac{\partial^2 Y}{\partial AI\,\partial L_S} = \frac{\partial}{\partial AI}\left(\frac{\partial Y}{\partial L_S}\right) = \alpha L_S^{\rho-1}\frac{\partial}{\partial AI}\left(Y^{1-\rho}\right).$$

Compute $\frac{\partial}{\partial AI}\left(Y^{1-\rho}\right) = (1-\rho)Y^{-\rho}\frac{\partial Y}{\partial AI}$. We need $\frac{\partial Y}{\partial AI}$. Compute $\frac{\partial Y}{\partial AI}$ by differentiating Y with respect to AI:

$$\begin{aligned}\frac{\partial Y}{\partial AI} &= \frac{\partial}{\partial AI}\left([\alpha L_S^{\rho} + (1-\alpha)L_H^{\rho}]^{\frac{1}{\rho}}\right)\\ &= \frac{1}{\rho}\left(\alpha L_S^{\rho} + (1-\alpha)L_H^{\rho}\right)^{\frac{1}{\rho}-1}\left((1-\alpha)\rho L_H^{\rho-1}\frac{\partial L_H}{\partial AI}\right)\\ &= (1-\alpha)L_H^{\rho-1}\left(\alpha L_S^{\rho} + (1-\alpha)L_H^{\rho}\right)^{\frac{1}{\rho}-1}\frac{\partial L_H}{\partial AI}\\ &= (1-\alpha)Y^{1-\rho}L_H^{\rho-1}\frac{\partial L_H}{\partial AI}.\end{aligned}$$

Compute $\frac{\partial L_H}{\partial AI} = (1-\beta)\theta L_{H,M}^{\beta}\left(L_{H,N} + \theta AI\right)^{-\beta}$.

Therefore,

$$\frac{\partial Y}{\partial AI} = (1-\alpha)(1-\beta)\theta Y^{1-\rho}L_H^{\rho-1}L_{H,M}^{\beta}\left(L_{H,N} + \theta AI\right)^{-\beta}.$$

Substitute back into $\frac{\partial^2 Y}{\partial AI\,\partial L_S}$:

$$\begin{aligned}\frac{\partial^2 Y}{\partial AI\,\partial L_S} &= \alpha L_S^{\rho-1}(1-\rho)Y^{-\rho}\left((1-\alpha)(1-\beta)\theta Y^{1-\rho}L_H^{\rho-1}L_{H,M}^{\beta}\left(L_{H,N} + \theta AI\right)^{-\beta}\right)\\ &= (1-\rho)\alpha(1-\alpha)(1-\beta)\theta Y^{1-2\rho}L_S^{\rho-1}L_H^{\rho-1}L_{H,M}^{\beta}\left(L_{H,N} + \theta AI\right)^{-\beta}.\end{aligned}$$

3. $\mathbf{\frac{\partial Y}{\partial L_{H,M}}}$:

$$\begin{aligned}\frac{\partial Y}{\partial L_{H,M}} &= \frac{\partial}{\partial L_{H,M}}\left([\alpha L_S^{\rho} + (1-\alpha)L_H^{\rho}]^{\frac{1}{\rho}}\right)\\ &= \frac{1}{\rho}\left(\alpha L_S^{\rho} + (1-\alpha)L_H^{\rho}\right)^{\frac{1}{\rho}-1}\left((1-\alpha)\rho L_H^{\rho-1}\frac{\partial L_H}{\partial L_{H,M}}\right)\\ &= (1-\alpha)L_H^{\rho-1}Y^{1-\rho}\frac{\partial L_H}{\partial L_{H,M}}.\end{aligned}$$

Compute $\frac{\partial L_H}{\partial L_{H,M}} = \beta L_{H,M}^{\beta-1}\left(L_{H,N} + \theta AI\right)^{1-\beta}$.

Therefore,

$$\frac{\partial Y}{\partial L_{H,M}} = (1-\alpha)\beta Y^{1-\rho}L_H^{\rho-1}L_{H,M}^{\beta-1}\left(L_{H,N} + \theta AI\right)^{1-\beta}.$$

4. $\mathbf{\frac{\partial^2 Y}{\partial AI\,\partial L_{H,M}}}$:

$$\frac{\partial^2 Y}{\partial AI\,\partial L_{H,M}} = \frac{\partial}{\partial AI}\left(\frac{\partial Y}{\partial L_{H,M}}\right).$$

Apply the product rule twice to receive:

$$\frac{\partial^2 Y}{\partial AI\, \partial L_{H,M}} = A + B + C,$$

where:

$$\begin{aligned}
A &= (1-\alpha)\beta \left(\frac{\partial Y^{1-\rho}}{\partial AI}\right) L_H^{\rho-1} L_{H,M}^{\beta-1} \left(L_{H,N} + \theta AI\right)^{1-\beta}, \\
B &= (1-\alpha)\beta Y^{1-\rho} \left(\frac{\partial L_H^{\rho-1}}{\partial AI}\right) L_{H,M}^{\beta-1} \left(L_{H,N} + \theta AI\right)^{1-\beta}, \\
C &= (1-\alpha)\beta Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta-1} \left(\frac{\partial}{\partial AI} \left(L_{H,N} + \theta AI\right)^{1-\beta}\right).
\end{aligned}$$

From 2. we have: $\frac{\partial Y^{1-\rho}}{\partial AI} = (1-\rho)(1-\alpha)(1-\beta)\theta Y^{1-2\rho} L_H^{\rho-1} L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta}$.
Compute $\frac{\partial L_H^{\rho-1}}{\partial AI} = (\rho-1) L_H^{\rho-2} \frac{\partial L_H}{\partial AI} = (\rho-1)(1-\beta)\theta L_H^{\rho-2} L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta}$.
Compute $\frac{\partial}{\partial AI} \left(L_{H,N} + \theta AI\right)^{1-\beta} = (1-\beta)\theta \left(L_{H,N} + \theta AI\right)^{-\beta}$.

Substitute back into A, B, and C:

$$\begin{aligned}
A &= (1-\rho)(1-\alpha)^2\beta(1-\beta)\theta Y^{1-2\rho} L_H^{2(\rho-1)} L_{H,M}^{2\beta-1} \left(L_{H,N} + \theta AI\right)^{1-2\beta}, \\
B &= (\rho-1)(1-\alpha)\beta(1-\beta)\theta Y^{1-\rho} L_H^{\rho-2} L_{H,M}^{2\beta-1} \left(L_{H,N} + \theta AI\right)^{1-2\beta}, \\
C &= (1-\alpha)\beta(1-\beta)\theta Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta-1} \left(L_{H,N} + \theta AI\right)^{-\beta}.
\end{aligned}$$

Therefore,

$$\frac{\partial^2 Y}{\partial AI\, \partial L_{H,M}} = A + B + C.$$

5. $\frac{\partial \mathbf{Y}}{\partial \mathbf{L_{H,N}}}$:

$$\begin{aligned}
\frac{\partial Y}{\partial L_{H,N}} &= \frac{\partial}{\partial L_{H,N}} \left([\alpha L_S^{\rho} + (1-\alpha) L_H^{\rho}]^{\frac{1}{\rho}}\right) \\
&= \frac{1}{\rho} \left(\alpha L_S^{\rho} + (1-\alpha) L_H^{\rho}\right)^{\frac{1}{\rho}-1} \left((1-\alpha)\rho L_H^{\rho-1} \frac{\partial L_H}{\partial L_{H,N}}\right) \\
&= (1-\alpha) L_H^{\rho-1} Y^{1-\rho} \frac{\partial L_H}{\partial L_{H,N}}.
\end{aligned}$$

Compute $\frac{\partial L_H}{\partial L_{H,N}} = (1-\beta) L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta}$.

Therefore,

$$\frac{\partial Y}{\partial L_{H,N}} = (1-\alpha)(1-\beta) Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta}.$$

6. $\frac{\partial^2 \mathbf{Y}}{\partial \mathbf{AI}\, \partial \mathbf{L_{H,N}}}$:

$$\frac{\partial^2 Y}{\partial AI\, \partial L_{H,N}} = \frac{\partial}{\partial AI} \left(\frac{\partial Y}{\partial L_{H,N}}\right).$$

Apply the product rule twice to receive:

$$\frac{\partial^2 Y}{\partial AI\,\partial L_{H,N}} = D + E + F,$$

where:

$$\begin{aligned}
D &= (1-\alpha)(1-\beta)\left(\frac{\partial Y^{1-\rho}}{\partial AI}\right) L_H^{\rho-1} L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta},\\
E &= (1-\alpha)(1-\beta)Y^{1-\rho}\left(\frac{\partial L_H^{\rho-1}}{\partial AI}\right) L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta},\\
F &= (1-\alpha)(1-\beta)Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta} \left(\frac{\partial}{\partial AI} \left(L_{H,N} + \theta AI\right)^{-\beta}\right).
\end{aligned}$$

We have already computed $\frac{\partial Y^{1-\rho}}{\partial AI}$ and $\frac{\partial L_H^{\rho-1}}{\partial AI}$.
Compute $\frac{\partial}{\partial AI}\left(L_{H,N} + \theta AI\right)^{-\beta} = -\beta\theta\left(L_{H,N} + \theta AI\right)^{-\beta-1}$.

Substitute back into D, E, and F:

$$\begin{aligned}
D &= (1-\rho)(1-\alpha)^2(1-\beta)^2\theta Y^{1-2\rho} L_H^{2(\rho-1)} L_{H,M}^{2\beta} \left(L_{H,N} + \theta AI\right)^{-2\beta},\\
E &= (\rho-1)(1-\alpha)(1-\beta)^2\theta Y^{1-\rho} L_H^{\rho-2} L_{H,M}^{2\beta} \left(L_{H,N} + \theta AI\right)^{-2\beta},\\
F &= -(1-\alpha)(1-\beta)\beta\theta Y^{1-\rho} L_H^{\rho-1} L_{H,M}^{\beta} \left(L_{H,N} + \theta AI\right)^{-\beta-1}.
\end{aligned}$$

Therefore,

$$\frac{\partial^2 Y}{\partial AI\,\partial L_{H,N}} = D + E + F.$$

Table A1: **CH Weighted Least Squares**

	Dependent variable:								
	soft					hard_manual		hard_non_manual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI_Jobs	0.112^{***}	0.012	0.002	0.009	0.042^{*}	-0.185^{***}	-0.044^{*}	0.072^{***}	0.003
	(0.009)	(0.016)	(0.021)	(0.021)	(0.022)	(0.020)	(0.024)	(0.010)	(0.015)
percentage_college		0.233^{***}	0.112	0.115	0.093		-0.153^{*}		0.060
		(0.034)	(0.081)	(0.081)	(0.066)		(0.085)		(0.051)
percentage_ind_manufacturing			-0.322^{**}	-0.327^{**}	-0.359^{***}		0.441^{**}		-0.082
			(0.153)	(0.153)	(0.136)		(0.178)		(0.086)
percentage_unemployed				-0.038	0.052		-1.151^{**}		1.099^{***}
				(0.552)	(0.554)		(0.554)		(0.231)
percentage_female_employment				-0.126	-0.094		0.104		-0.011
				(0.142)	(0.130)		(0.132)		(0.074)
percentage_over65					0.459^{*}		-0.153		-0.306^{***}
					(0.258)		(0.201)		(0.118)
Observations	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068
R^2	0.259	0.293	0.298	0.299	0.305	0.409	0.479	0.261	0.314
Adjusted R^2	0.241	0.275	0.279	0.279	0.284	0.395	0.464	0.243	0.293

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All configurations include year and large labor market area fixed effects. Standard errors are clustered at the labor market area level.