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IZA DP No. 15687

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ABSTRACT

Education Expansion and High-Skill Job Opportunities for Workers: Does a Rising Tide Lift All Boats?*

We examine how education expansions affect the job opportunities for workers with and without the new education. To identify causal effects, we exploit a quasi-random establishment of Universities of Applied Sciences (UASs), bachelor-granting three-year colleges that teach and conduct applied research. By applying machine-learning methods to job advertisement data, we analyze job content before and after the education expansion. We find that, in regions with the newly established UASs, not only job descriptions of the new UAS graduates but also job descriptions of workers without this degree (i.e., middle-skilled workers with vocational training) contain more high-skill job content. This upskilling in job content is driven by an increase in high-skill R&Drelated tasks and linked to employment and wage gains. The task spillovers likely occur because UAS graduates with applied research skills build a bridge between middle-skilled workers and traditional university graduates, facilitating the integration of the former into R&D-related tasks.

JEL Classification: I23, J23, J24

Keywords: educational expansion, worker demand, upskilling, spillover effects, vocational training

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Job requirements have considerably risen over the last four decades, with jobs demanding more skill and more education to handle sophisticated tasks (Alekseeva et al., 2021; Atalay et al., 2020; Hershbein and Kahn, 2018). Automation and digitalization likely push these requirements to even higher levels (Autor, 2015). The increase in requirements applies particularly to jobs in science, technology, engineering and mathematics (STEM) that involve increasingly sophisticated research and development (R&D) tasks (Carnevale et al., 2011; Grinnis, 2019; Wilson, 2009). As many workers grapple with these increased job requirements, the question of how to prepare the workforce for these new and complex jobs of a technology-driven economy has attracted much attention among researchers and policymakers. One commonly discussed policy measure is the expansion of tertiary education (Chowdry et al., 2013; Kyui, 2016; Vella and Gregory, 1996).

However, the effect of tertiary education expansion on the job opportunities of tertiary graduates on the one side and particularly of middle-skilled workers (without the new tertiary degree) on the other side remains unclear. One strand of research argues that a rising number of tertiary graduates pushes the middle-skilled workers without tertiary degrees down the job ladder (Hansson, 2007), forcing them into less skilled, less attractive, and less well-paid jobs (Dupuy, 2008, 2012; Rosen, 1978; Sattinger, 1975). Conversely, another strand of research argues that an expansion of tertiary education will generally increase productivity and innovation in firms (Mansfield and Lee, 1996; Toivanen and Väänänen, 2016; Valero and van Reenen, 2019; Grosz, 2020), which would even enable middle-skilled workers to advance into jobs with more skilled tasks.

In this context, we examine a new type of tertiary education institutions—the Universities of Applied Sciences (UASs) in Switzerland—that uniquely offer a new career path for middle-skilled workers (with vocational training), leading them to the tertiary level. UASs in Switzerland are bachelor-granting three-year colleges that target middle-skilled workers and focus on teaching and conducting applied research. We study whether not only the graduates of the newly established UASs gain by advancing into jobs with more sophisticated tasks but also those middle-skilled workers without the new UAS degree. With technology becoming more and more important for economic success and with job requirements rising in technical occupations (Beede et al., 2011; Carnevale et al., 2011; Grinnis, 2019), we concentrate on UAS campuses in STEM fields. UAS graduates in STEM have the strongest link to innovation tasks and new technologies (as opposed to, for example, social work or health, which have much weaker links). It is crucial to study how vocationally trained workers in STEM fields have been affected by the establishment of UASs, which had the goal to prepare them for the requirements of a technology-driven economy and to foster innovation.

As we are interested in how a supply shock at the tertiary education level affects the job opportunities particularly for those workers remaining at their initial education level and without the new UAS degree, we examine changes in job content for workers given a fixed educational level. Conceptually, we define upskilling as an increase in skill requirements on the job and as a move towards more sophisticated tasks within educational levels (e.g., the vocational level) and occupations (i.e., more sophisticated tasks for workers within certain occupations).[1]

To assess upskilling empirically, we examine the job descriptions in job advertisements, following the increasingly used method of analyzing job advertisements for capturing job content (Alekseeva et al., 2021; Atalay et al., 2020, 2018; Deming and Kahn, 2018; Deming and Noray, 2020). In particular, we apply natural language processing (NLP) methods (Gentzkow et al., 2019; Le and Mikolov, 2014) for text vectorization to job descriptions and measure the textual similarity to a benchmark of high-skill jobs. Additionally, we examine the

[1] We view upskilling to be conceptually different from "educational upgrading," which many studies define as a demand by firms for workers with higher education levels and credentials (Virdia and Schindler, 2019; Oesch and Rodríguez Menés, 2010; Modestino et al., 2020). Our view of upskilling is closer to, for example, Hershbein and Kahn (2018), who examine changes in skill requirements within occupations.

frequency of R&D-related main tasks because these are the tasks that best reflect the goal of UASs to boost innovation. Moreover, these tasks are highly complex and require great amounts of worker autonomy. We define tasks that meet these requirements and contain applied R&D activities (i.e., researching, programming, and engineering) as "R&D-related tasks."

As data source we draw on the Swiss Job Market Monitor (SJMM), a large representative sample of print and online advertisements for job vacancies (hereafter, "job ads") (Buchmann et al., 2017). As educational pathways in Switzerland are highly structured and closely associated with jobs in specific occupations, job ads are clearly targeted at specific educational and occupational groups, allowing us to precisely examine the job opportunities for workers from different educational backgrounds.

To solve the endogeneity problems usually associated with education expansions, we exploit the establishment of UASs in Switzerland in the late 1990s as a quasi-random natural experiment (as used in Pfister et al., 2021, Lehnert et al., 2020, and Schlegel et al., 2022). Before the establishment of UASs, job descriptions in treated regions (i.e., with later established UASs) and control regions (i.e., with no established UASs) shared the same trend. This shared trend supports the assumption of quasi-randomness in the establishment process. We exploit the quasi-randomness in the location and timing of UAS campus openings with an event study design (Bismarck-Osten et al., 2021; Jaeger et al., 2021; Borusyak et al., 2021).

Our results indicate a positive impact on the first-order outcomes of the tertiary education expansion (i.e., outcomes of the new type of tertiary graduate): Firms in treated regions seek the new UAS graduates for high-skill jobs. We therefore argue that graduating from a UAS enables individuals to climb not only the educational ladder, but also the job ladder. Furthermore, our results also show significant effects on second-order outcomes (i.e., outcomes of workers that remain without the new tertiary degree) and provide strong evidence for also elevating this educational group: Job descriptions for vocationally trained workers (we use "vocationally trained workers" to refer to those workers with a vocational diploma but without the new UAS degree) become substantially more similar to the high-skill benchmark. Further analyses reveal that the increased similarity is strongly linked to a higher share of R&D-related tasks in the task profiles of vocationally trained workers after the establishment of UASs.

Placebo tests support the UASs as the causal driver of the upskilling effects: Only vocationally trained workers in STEM fields (with a clear link to a UAS STEM education) experience upskilling; vocationally trained workers in non-STEM fields (i.e., the "placebos," such as occupations in health, business, or social work) do not experience any upskilling through the education expansion.

To examine whether the upskilling in job content transfers into tangible labor market improvements for vocationally trained workers, we rely on two additional data sources—the Swiss Earnings Structure Survey (SESS) and the Swiss Labor Force Survey (SLFS)—and estimate effects on two traditional labor market outcomes (i.e., wages and employment). The results support our key findings from the job content analyses. First, based on the SESS firm-level data, we find that firms not only seek more but also employ more vocationally trained workers in high-skill R&D-related jobs, confirming the upskilling of these middle-skilled workers. Second, based on the SLFS worker-level data, we find that vocationally trained workers experience higher wages in treated regions, suggesting the upskilling in job content transferred into substantial wage gains. In sum, from three independent data sources we find strong evidence for upskilling after the education expansion—even of those workers that remain at the middle-skill level but then gain from positive spillovers from workers with the new degree. Moreover, our findings demonstrate that these spillovers are not restricted to job content but also manifest as positive employment and wage spillovers, indicating tangible benefits from the UAS education expansion.

How can one explain these results? We argue for and provide evidence consistent with a mechanism in which the new UAS graduates act as bridge builders between middle-skilled vocationally trained workers and high-skilled graduates from academic universities (for brevity, we refer to them as “academic graduates”). UAS graduates possess (a) sound occupational training (from their vocational background) that allows them to build the connection to the vocationally trained workers and (b) applied research skills (from the UAS education) that allow them to build the connection to the typical R&D worker, trained in basic research at an academic university. Vocationally trained workers can then benefit from the presence of UAS graduates, who—as bridge builders—enable a more efficient combination of diverse skill sets, which is crucial for high-skill tasks in R&D processes.[2]

This study contributes to three strands of literature: First, by examining the effects of an educational supply shock in STEM fields on the jobs of middle-skilled workers, we contribute to the literature examining labor supply shocks and the consequences for firms and workers (Acemoglu, 1996, 2007; Beaudry and Green, 2003; Blundell et al., 2018; Carneiro et al., 2018; Moretti, 2004; Stuen et al., 2012). Second, while the larger literature on demand-driven shocks finds substitution effects for middle-skilled workers, leading to job polarization (Autor et al., 2003; Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2009; Michaels et al., 2014), we demonstrate an opposite effect after a supply-driven shock, that is, an upskilling of middle-skilled workers. Third, by introducing a new text-based upskilling measure, we contribute methodologically to the growing economic literature that uses text as data for exploring labor market phenomena (Atalay et al., 2018; Deming and Kahn, 2018; Hershbein and Kahn, 2018; Michaels et al., 2018; Sahin et al., 2014). Based on NLP techniques for text vectorization (Bengio et al., 2006; Collobert and Jason, 2008; Turian et al., 2010; Le and Mikolov, 2014; Gentzkow et al., 2019), this new measure allows researchers to overcome problems of both synonyms in job ads (e.g., “investigating” and “examining”) and changes in

[2] Without UAS graduates, the gap between workers with an academic degree and a vocational diploma is much larger, causing nonnegligible communication costs that prevent firms from efficiently combining such skills for R&D processes. As a consequence, firms lose out on innovative solutions such as building prototypes or testing-devices that strongly require both skill sets (as, for example, shown by case studies provided in Backes-Gellner and Pfister, 2019).

word use over time that do not reflect changes in meaning (e.g., "close collaboration" and "teamwork").

The paper proceeds as follows: Section I discusses the theoretical background of how tertiary education expansion affects the job opportunities for workers with and without tertiary education degree. Section II describes the data and explains the construction of our upskilling measure. Section III presents methodology and findings for first-order outcomes (i.e., of UAS graduates), while Section IV shows our methodology and findings for second-order outcomes (i.e., of vocationally trained workers). Section V reports the results from analyzing employment and wages as additional second-order labor market outcomes. Section VI explores bridge building as the potential mechanism underlying our main findings. Section VII concludes.

I. Tertiary Education Expansion and Job Opportunities: Theoretical Considerations and Hypotheses

The availability of a new type of high-skilled workers (such as UAS graduates) may have two effects on job opportunities: (a) firms create new jobs with tasks suited for the skills of that new type (as first-order outcomes) and (b) firms restructure the task allocation in jobs for other types of workers (as second-order outcomes). This restructuring can take the form of either crowding out skilled tasks (i.e., downskilling) according to assignment models (e.g., Acemoglu and Autor, 2011; Rosen, 1978; Sattinger, 1975) or adding skilled tasks (i.e., upskilling) to better match existing jobs with the newly created jobs according to organizational models (e.g., Garicano and Rossi-Hansberg, 2006; Lazear, 1999; or McCann et al., 2015). The direction of the effect on second-order outcomes thus remains theoretically ambiguous.

Crowding out.—In assignment models of comparative advantage, firms maximize overall output by partitioning tasks among different types of workers, with each type of worker performing a bundle of tasks called a "job" (for a comprehensive survey of the literature, see Sattinger, 1993, and Dupuy, 2008). As the optimal allocation of types of workers to tasks follows the logic of comparative advantage, firms assign types of workers to tasks for which these types are relatively more capable (Acemoglu and Autor, 2011; Dupuy, 2008, 2012; Sattinger, 1975; Teulings, 1995, 2005). Therefore, after a high-skilled labor supply shock, firms seek the new high-skilled workers for high-skill tasks (first-order outcome). However, in a static model, these tasks stem partly from a reallocation of tasks originally allocated to less-skilled workers (Costrell and Loury, 2004). The restructuring and reallocation of tasks to high-skilled workers thus result in a crowding out of those tasks and downskilling for less-skilled workers (second-order outcomes).

Applied to the effects of the establishment of UASs, the graduates of these institutions have a comparative advantage in high-skill R&D-related tasks, for which firms would therefore seek and employ them (as first-order outcomes). In a static model, firms would thus reallocate the tasks of middle-skilled workers and assign them to fewer of these high-skill tasks (second-order outcomes). In this case, we thus expect a crowding out of skilled tasks, such as contributing to R&D processes, and downskilling for the middle-skilled workers.

Upskilling.—Organizational models assume that the combination of tasks for producing output requires different workers to coordinate and communicate (for an overview, see Garicano and Rossi-Hansberg, 2015). Workers encounter frictions when working in teams and combining tasks (Deming, 2017; Lazear, 1999), with communication and coordination necessary for overcoming those frictions (McCann et al., 2015; Morris and Shin, 2007). Therefore, exploiting complementarities (e.g., from different sources of knowledge) and realizing the gains from comparative advantage (e.g., from different skill sets) requires different types of workers to be able to effectively communicate with one another (Garicano and Wu, 2012; Garicano and Rossi-Hansberg, 2006, 2004; Lazear, 1999). Some types of workers may be particularly qualified for this communication task, e.g., by being either bilingual in occupation-specific terminology or well-versed in different cultures (socioeconomic or departmental) or fields of work (technical or administrative) (Lazear, 1999).

Educationally diverse teams can benefit from complementarities but may also create additional costs if communication difficulties cannot be solved (Kurtulus, 2011). Applying this reasoning to the situation before and after the establishment of UASs, we expect the following effects. Before the establishment of UASs (i.e., in a situation without UAS graduates), larger educational gaps existed between high-skilled workers (academically trained) and middle-skilled workers (with vocational education). Both groups underwent education in two completely separate systems with their own educational conventions, professional languages, and work styles. This gap caused non-negligible communication and coordination costs for teamwork, particularly in R&D processes which require both groups' knowledge and experience for reaching optimal outcomes.

The UASs introduced a new educational career path for middle-skilled workers, which builds on and complements their preexisting skill set from their vocational background with applied research skills. UAS graduates therefore have an education that overlaps both that of academic graduates and vocationally trained workers. This overlap enables UAS graduates to act as bridge builders and communicators between the two groups, reducing communication and coordination costs in teams.

After the establishment of UASs, firms can then hire the new graduates to bridge the gap between vocationally trained workers and academically trained university graduates for their R&D processes. UAS graduates help to promote teamwork across different educational levels in the R&D process and facilitate the creation of new R&D-related tasks among vocationally trained workers (e.g., building testing devices or prototypes).[3] The presence of UAS graduates thus enhances the overall efficiency of R&D processes, enabling firms to expand their R&D efforts. According to this dynamic explanation, the presence of UAS graduates raises the innovation and R&D efforts by firms, resulting in more skilled tasks even

[3] The idea of a shared background facilitating teamwork can also be found in the psychology literature (Mathieu et al., 2000; Mohammed et al., 2010; Mohammed and Dumville, 2001; Stout et al., 1999).

for middle-skilled workers without a UAS degree (as second-order outcomes). Following this reasoning, we expect upskilling for middle-skilled vocationally trained workers after the establishment of UASs.

While the assignment and organizational literatures derive unambiguous theoretical predictions for the first-order outcomes (i.e., firms seeking UAS graduates for high-skilled tasks such as R&D-related tasks), the predictions for the second-order outcomes are contradictory, i.e., task restructuring may lead to either a crowding out or an addition of skilled tasks to the jobs offered to vocationally trained workers. To solve this puzzle empirically, we require detailed information from job ads on the tasks for which firms want to hire workers before and after the establishment of UASs.

II. Data and Descriptives

A. *The Swiss Job Market Monitor*

The Swiss Job Market Monitor (SJMM) offers precise data for capturing job opportunities (Buchmann et al., 2017). The SJMM is based on a representative sample of job ads for Switzerland from 1950-2016. The SJMM sample is collected annually and stratified over advertising channels (e.g., newspapers, firm websites) and the characteristics of the advertising media within each channel (e.g., the print run of a newspaper). In contrast to the job vacancy data previously used in the literature (e.g., Deming and Kahn, 2018; Hershbein and Kahn, 2018), the SJMM not only contains job ads over a longer period (1950 - 2016) but also covers the entire range of media relevant to the job market: newspapers, online job boards, and firm websites. Moreover, the SJMM data comes in a preprocessed form and offers high-quality text data as the SJMM team manually typed the text and hand-coded the characteristics of each job ad, that is, the job ads in the dataset contain no missing elements (Buchmann et al., 2017).[4]

The use of job ads as a source of information for capturing job opportunities has several advantages: Job ads share a common information structure. Rafaeli and Oliver (1998) call this information structure a "skeleton" that all job ads share. Every job ad contains information about the identity of the firm, its human resource needs, its requirements for fulfilling those needs, and the firm's contact information. The similarity to this structure makes both the categorizing and the comparing of job ads possible. Job ads also mirror firms' needs at the local level. This property enables us later to capture at small geographic levels, such as the municipality level, how job opportunities were affected by the UASs.

The SJMM builds on the common information structure of job ads and offers two distinct classes of information: First, a manual coding for the main characteristics of each job ad. Second, the full text of each job ad, with a textzone classification grouping—based on supervised machine learning—words according to their function in the text.

Our empirical analyses require for each job ad information on the necessary formal education[5] (i.e., whether the job position targets vocationally trained workers, UAS graduates, or academic graduates), the occupation (i.e., whether the occupation is from a STEM or non-STEM field), and the geographic location of the workplace (i.e., we can identify whether the vacancy is in a region with or without a UAS campus). The manual coding by the SJMM delivers all this information, enabling us to differentiate between job opportunities for

[4] The SJMM team started collecting job vacancy data in 2001 (also retrospectively, i.e., back to 1950). As the technology for optical character recognition (OCR) (required for digitalizing for large amounts of print data) was unavailable at that time, the SJMM collected and sampled job ads from newspaper archives and then manually typed the content of each job ad into a digital format. Given this procedure, the SJMM contains no missing or falsely classified elements.

[5] As in Switzerland the education system is clearly structured, firms *commonly* and *explicitly* state the required education and training requirements for open job positions—and applicants are expected to match this requirement with their formal educational degree. In our data, the vast majority of job ads targets either workers with upper-secondary vocational education or workers with tertiary education but rarely both at the same time. Only 152 out of 6,784 obs. of the job ads in our sample of vocationally trained workers contain overlapping educational requirements (i.e., firms accepting applications from both workers with a vocational diploma and those with a UAS degree). Excluding them from our regression sample does not alter our results.

vocationally trained workers and UAS graduates and to investigate changes in the local job opportunities after campus openings.

Additionally, the SJMM contains the full text for the sampled job ads and a textzone classification for them, making it a powerful data source for precisely measuring the tasks that firms want to hire workers for. Based on supervised machine learning, job ad text is structured into eight categories (called textzones), such as the job description, the firm description or the required hard and soft skills (Gnehm, 2018). The eight textzones reflect the structure of a typical job ad. In our study, we focus on the job description because it contains the tasks and characteristics of the advertised job position: for example, R&D-related activities ("analyzing"), use of software ("Python"), or modes of organization ("teamwork"). Furthermore, for examining the hypothesized bridge-building mechanism, we utilize the textzone for soft skills (e.g., being "communicative" or a "teamplayer"). Figure 1 illustrates the application of the textzone algorithm.

[Figure 1]

We examine job ads only from the German-speaking part of Switzerland (covering 70 percent of the population and 72 percent of GDP) because the SJMM sample is limited to the German-speaking part of the country before 2000 and our analyses require job ads before 2000 (the establishment of UASs started in 1997). Additionally, as the textzone algorithm is only trained for job ads in German, it cannot be used for job ads that are in French or Italian and come from the other parts of Switzerland. Furthermore, we focus on the establishment of UASs in the German-speaking part because educational traditions differ between the German-speaking part, where vocational education has much stronger roots, and the French- and Italian-speaking parts of Switzerland, where this type of education has weaker roots and the establishment of UASs would therefore require separate empirical analyses.[6]

B. *Identification and Treatment Definition*

Capturing the effects of tertiary education expansion on task demand requires not only an appropriate database but also quasi-random variation in the availability and expansion of tertiary education institutions. The establishment of UASs in Switzerland in the 1990s took the form of a natural experiment that provides us with the required quasi-random regional and temporal variation in educational supply at the tertiary level, i.e., UAS graduates (Lehnert et al., 2020; Pfister et al., 2021). The magnitude of the educational expansion was substantial and constituted an important intervention in the tertiary education sector (in 2010, 8,538 students graduated from a UAS with a Bachelor's degree versus about 11,536 students with a Bachelor's degree at a traditional academic university; Swiss Federal Statistical Office, 2022).

To reconstruct the establishment process of UASs and their campuses, Pfister et al. (2021) thoroughly analyzed a large number of reports, official statements, and position papers from all stakeholders involved in the process. Moreover, they closely examined official bulletins and chronicles, documents on the legislation process, annual reports of UASs, and articles from newspapers (more than 100 articles from 16 different newspapers) in the relevant observation period. Pfister et al. (2021) show that the establishment process of UASs was driven by a large number of random political factors. Due to Switzerland's federal political system—in which cantons (much like U.S. states) have a high degree of policy-making autonomy while sharing political power with the federal government—the timing and location decisions of UAS campus openings were the result of political trench warfare between and within cantons. Micro-

[6] The French- and Italian-speaking (Latin) part is mainly situated in the (south)western regions of Switzerland, with language, culture, and educational traditions differing from the German-speaking part (Eugster et al., 2011). We follow the argument by Pfister et al. (2021) of focusing on the German-speaking part of the country, in which the training of apprentices and the UASs as an educational option are most prevalent.

politics, concessions, package deals across a large variety of policy fields, and coincidences drove the establishment process, making the timing and locations of UAS campuses both unforeseeable and quasi-random from an economic perspective.

We study UAS campuses specializing in chemistry, the life sciences, engineering, and IT (in total 15 STEM campuses) because we are interested in academic fields that closely relate to a technology-driven economy and innovation (one of the main goals of UAS establishment was to boost innovation). The STEM campuses conduct applied R&D and provide their students with the necessary applied R&D skills for their future jobs. Even though the establishment of new UAS campuses also involved campus openings in non-STEM fields (for example, four campuses in health and eight in social work), we focus in our empirical analyses only on the effects of STEM campuses as we consider spillovers between different campus fields to be very unlikely. The reason is that UASs require students to have professional experience in the field that they intend to enroll in (i.e., study programs at STEM campuses require a vocational education and/or prior working experience in a STEM or technical occupation). Consequently, there are almost no cross-connections between UAS campuses in STEM and non-STEM fields, and UAS graduates are practically "locked in" to their original vocational field. We therefore expect spillovers between STEM and non-STEM fields to be highly unlikely. Restricting our sample to STEM graduates and STEM campuses enables us to keep the analysis as focused as possible on the original goal of the UAS establishment.

To empirically capture the effect of UASs on job opportunities, we need to link our main sample of job ads to the timing and location of UAS campus openings. We use the information from Pfister et al. (2021) on when and where each of the new UAS campuses was established. The establishment process took the form of a staggered rollout, with the earliest campuses opening in 1997 and the most recent campus in 2003. Given that students need a minimum of three years to graduate from a bachelor's program at a UAS, we assume that UAS graduates enter the local labor market three years after the establishment year and can then have an effect on job ads. We exploit the spatial and temporal variation resulting from the staggered rollout of UAS campus openings.

To define whether a firm with a job opening was treated by the opening of a UAS campus, we follow Pfister et al. (2021) and take a regional approach, i.e., assuming that all firms geographically close to a new UAS campus are treated. Similar to Pfister et al. (2021), we assume that the effect of UASs is geographically limited because Swiss graduates are rather immobile and commute comparatively short distances. To determine the treatment status of each job ad, we use information on the location of the workplace, that is, the municipality ("Gemeinde") in which the establishment with the vacancy is located. As almost 90 percent of all employees commute less than 25 kilometers (roughly 15 miles) from home to work (Pfister et al., 2021), we study job ads within catchment areas of 25 kilometers (roughly 15 miles) around newly established UAS campuses. Our treatment group consists of job ads in municipalities within the 25 km catchment area, whereas the control group contains job ads outside these areas (see Figure A1 in Appendix A for a map that shows the geographic location of UAS campuses in STEM and illustrates the catchment areas with an example).

C. *Outcome Variable: Textual Similarity*

For measuring upskilling effects in the task content, we apply a textual similarity measure to job descriptions and capture how textual similar the job descriptions of different educational groups are to a high-skill benchmark. We use the job descriptions for academic graduates as a realistic high-skill benchmark because their descriptions are for typical high-skill jobs. Moreover, these job descriptions provide a good text benchmark, because they are the most elaborate, covering a wide range of words describing the job (e.g., "contact with clients"), the technology used (e.g., "Python"), and the activities required (e.g., "coordination"). The textual similarity measure utilizes all this information at the word level and reduces all facets of job content to one dimension, elegantly capturing the skill level of the described job and enabling us to measure up- and downskilling.

When constructing the similarity measure over long periods, we face problems typically associated with text analyses over longer periods, such as the challenge of the evolving meanings of words. For example, in certain industries and occupations (e.g., consulting), firms frequently use management buzzwords that change over time. Consequently, word changes may only reflect changes in vocabulary but not actual changes in meaning. A similar problem arises for STEM jobs, which are characterized by technological progress that rapidly changes job descriptions and the words identifying upskilling (Deming and Noray, 2020). For example, both ten-year-old computer technologies and their names are now outdated (e.g., Objective C is now replaced by Swift). To tackle such challenges, we construct a dynamic yearly measure, based on text vectors, that we generate from the data as opposed to imposing a static keyword measure. To vectorize our text data, we draw on the "doc2vec" algorithm as an advanced natural language processing (NLP) technique (Le and Mikolov, 2014; Gentzkow et al., 2019; Burn et al., 2019).

Vectorizing the job descriptions enables us to deal with both an evolving vocabulary over time and the problem of synonyms. We use the lemmatized[7] version of the job description (while also removing "stop words" such as "at," "which," and "and," and other potential confounders such as placeholders) and then apply the doc2vec algorithm (Le and Mikolov, 2014). Doc2vec is an unsupervised machine-learning algorithm that learns vector representations for variable-length text pieces such as job descriptions. In our model, each job description is characterized by a vector of 100 dimensions that locates the job description in the space of meaning. The doc2vec algorithm trains neural networks with a fake task: Given a random word (from all job descriptions), the neural net has to predict the remaining words of

[7] A lemma is the dictionary form of a set of words. For example, "develop" represents the lemma for "develop," "developed," "develops," and "developing." Lemmatization involves syntactical and morphological analysis, therefore offering better precision than stemming (i.e., reducing words to their word stem). We use TreeTagger (Schmid, 1995) for the lemmatization of job ad texts.

each job description. The algorithm is based on the distributional hypothesis: Words appearing in a similar context share a similar meaning (e.g., "investigate" and "look into" often appear in the same context and thus share a similar meaning). Consequently, the algorithm first assigns semantically similar words to similar word vectors (as they appear in the same context) and, second, similar job descriptions to similar text vectors.[8]

Drawing on the text vectors for the job descriptions, we create for each year a representative job description for academic graduates and then measure the similarity of the other job descriptions to this benchmark (hereafter, we call this measure "similarity to job descriptions of academic graduates").[9] We calculate the cosine similarity, which is commonly used in computational linguistic research (Gomaa and Fahmy, 2013). It measures the cosine of the angle between the two vectors (i.e., whether they point in the same direction) and ranges between -1 and +1, with a zero implying orthogonality and higher values indicating higher similarity (Appendix C provides examples of job ads and their similarity with the high-skill benchmark). If the job descriptions for an educational group become more similar to the high-skill benchmark, we interpret this change as upskilling. However, if the job ads become less similar, we assume that this change is a crowding-out effect of skilled tasks (downskilling).

To validate this textual similarity measure and better understand, what kinds of tasks are linked to changes in similarity, we use the manually coded "main task" category from the SJMM. The SJMM defines the main task as the category of tasks that the job ad highlights the

[8] The supervised machine-learning algorithm for the textzoning classification is trained only for job ads in German. These job ads represent 94.87 percent of all job ads in our sample, with job ads in other languages constituting 5.13 percent. Job ads in other languages, usually from internationally operating employers, contain a much higher percentage of skilled tasks and leaving them out would restrict our sample's representativeness and bias our results. Therefore, we need to find a way to take them into consideration despite their different language. However, automatically translating job ads across different languages remains a methodologically unanswered question (e.g., whether jargon is being correctly captured and how technical terms are being translated). Therefore, we use a matching procedure as a second-best solution. We use the manually coded characteristics of these job ads to match them to "twin" job ads (i.e., with the same occupation and the same main task) in German. We assume that the foreign language job ads have the same text characteristics (i.e., numeric textzone vectors) as their German counterparts. In so doing, we are able to include these job ads in our sample and use them for estimating the effects from the establishment of UASs. However, future research could expand this approach and apply it to cross-country analyses by translating job ads with a machine translation program and by carefully assessing and verifying the translation results.

[9] To generate the benchmark, we take the mean of the job description vectors from job ads targeting academic graduates in the same year. The benchmark thus represents the job content described in the average academic job ad. To avoid compositional changes in the benchmark and to have a clean comparison later for our subsample analyses and placebo test, we calculate the benchmark separately of academic STEM and academic non-STEM jobs. Moreover, to avoid potential indirect effects such as the UASs potentially affecting the jobs of academic graduates in the local labor market, we use a nationwide academic job benchmark, i.e., the benchmark is always the same for treatment and control group. We apply these definitions consistently throughout the entire observation period of our sample.

most in the text. Each job ad has only one main task. The main task is one of 21 distinct categories, ranging from agricultural tasks or sales and customer service to publishing and creative work. This categorization of the main task both follows and augments a task categorization that the German Socio-Economic Panel (Stoss and Weidig, 1990) used in their questionnaires. Müller and Buchs (2014) find a good reliability of the main task encoding, with a Krippendorff's alpha of 0.76. Table 1 provides an overview of the descriptive statistics over our variables of interest, including the main tasks.

[Table 1]

Table 2 shows how these manually coded tasks correlate with our textual similarity measure of upskilling. The appearance of high-skill tasks such as *IT & Programming* and *Analyzing & Researching* is strongly positively correlated with our text-based upskilling measure, whereas low-skill tasks such as *Warehousing & Transport* or *Sales & Customer Service* are strongly negatively correlated with it. These correlations show that differences in textual similarity across job ads reflect actual differences in the tasks that workers will perform in the respective job. In our empirical analyses, we additionally examine changes in the main tasks and, in particular, check whether the effects of the UAS establishment on textual similarity with the high-skill benchmark also materialize as changes in R&D-related main tasks.

[Table 2]

III. Descriptive Evidence on First-Order Outcomes:- Job Content of UAS Graduates

For investigating changes in job content for UAS graduates, we cannot make before-after comparisons. Instead, we can inevitably only examine job ads targeting UAS graduates after the UASs had already been established and the first graduates entered the labor market (i.e., jobs for UAS graduates or for a comparable type of tertiary education did not exist before the establishment of UASs). We thus provide descriptive evidence on the type of jobs that firms actually intend to hire this new type of tertiary graduate for. We refer to these outcomes as "first-order outcomes."

We descriptively analyze the job characteristics for UAS graduates and our findings indicate high-skill job opportunities for this new type of graduate. The jobs for UAS graduates are closer to the jobs of high-skilled academic graduates (compared to jobs advertised for vocationally trained workers, i.e., the job opportunities without a UAS degree). Job descriptions for UAS graduates are textually 19 percent more similar to the high-skill benchmark, compared to the job descriptions of vocationally trained workers. Graduation from a UAS is thus associated with jobs that are closer to the high-skill benchmark. Our results therefore suggest that vocationally trained workers who graduate from a UAS not only advance to the next higher educational level but also climb the job ladder.

In a next step, we show that this increased similarity of jobs with academic graduates is likely driven by firms seeking UAS graduates (and their applied research skills) for tasks typically needed in firms' R&D processes. As the goal of the establishment of UASs was to boost innovation, UAS graduates being sought after for R&D-related tasks is an important finding.

[Table 3]

Table 3 displays the ten most frequent main tasks that firms mention when searching for UAS graduates, with the R&D-related main tasks of *Analyzing & Researching*, *Engineering & Designing*, and *IT & Programming* being among the most frequent ones. The high frequencies of these tasks show that UAS graduates with their newly acquired applied research skills are indeed integrated into a broad spectrum of R&D activities. Graduating from a UAS thus opens up a new range of jobs, different from the middle-skilled jobs for vocationally trained workers and closer (albeit not identical) to those of academic graduates. These upskilling findings then raise the question of whether the advancement of UAS graduates comes at the cost of those vocationally trained workers who are remaining without the new tertiary degree.

IV. Second-Order Ootcomes: Job Content of Vocationally Trained Workers

A. *Event Study Design*

To estimate the effect of the establishment of UASs on the job opportunities of vocationally trained workers without the new degree (the effect on second-order outcomes), we use an event study design that exploits the temporal and regional variation in the staggered rollout of UAS campuses. The following equation shows our underlying model, with the level of observation being job ad i (located in catchment area c and posted in year t):

$$Upskill_{i,c,t} = \alpha_c + \beta_t + \sum_{p=-6}^{10} \gamma_p \, 1[t = E_c + p]_{c,t} + Channel_{i,c,t} + \varepsilon_{i,c,t} \quad (1)$$

The outcome of interest is $Upskill_{i,c,t}$, capturing the textual similarity of job ad i with the high skill benchmark. As our data structure is a repeated cross-section, we use catchment area fixed effects α_c and time fixed effects β_t to control for time-invariant differences across catchment areas and underlying time trends. The treatment variables of interest are a set of event study indicators $1[t = E_c + p]_{c,t}$ taking the value of 1, when the event E_c of the first new UAS graduates entering the catchment area c is p years away.

To estimate the event study coefficients, we use the event study estimator of Borusyak et al. (2021). A growing literature discusses the problems that arise for estimators leveraging difference-in-differences contrasts in settings of staggered rollouts with dynamic treatment effects (Callaway and Sant'Anna, 2021; Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, forthcoming). Moreover, standard event study estimators can be prone to underidentification of longer-run effects (Borusyak et al., 2021; Borusyak and Jaravel, 2017). The event study estimator by Borusyak et al. (2021) offers improved efficiency and robustness under potential treatment heterogeneity and—with a completely unaffected control group—allows us to credibly estimate longer-run effects beyond the initial rollout (Bismarck-Osten et al., 2021; Jaeger et al., 2021). The estimator captures time and unit fixed-effects based only on untreated observations, thereby circumventing the issue of mixing in "forbidden" difference-in-differences contrasts (i.e., using earlier treated units as quasi controls).[10]

We set our observation period to job ads from 1995 to 2010. As manually coded information on main tasks in the SJMM is available from 1995, we use 1995 as our first year of observation. However, with information lacking on the long-run mobility of UAS graduates, we end our observation period in 2010 to avoid contamination issues that may arise from UAS graduates beginning to move in the longer run.[11] Restricting our sample from 1995 to 2010, we have the six years before the first UAS graduates entered the labor market as pretreatment periods and 10 years after as posttreatment periods.

Given that from 1995 to 2010 the practices of advertising job vacancies changed, we use the information on the advertising channel of each job ad as an additional control variable (denoted as $Channel_{i,c,t}$). Before 2001, the SJMM sample contained only job ads from newspapers. From 2001, it also includes job vacancies that firms announce on their business websites and, from 2006, also captures those vacancies that firms post on online job boards.[12]

[10] Borusyak et al. (2021) argues that estimating pre- and posttreatment effects separately provides a cleaner methodology for examining the common trend assumption, because the approach separates the steps of making an identifying assumption and validating it. We follow the approach by Borusyak et al. (2021) and also estimate pre- and posttreatment effects separately.

[11] In-migration and out-migration from treatment and control groups are a potential concerns, when examining the effects of tertiary education expansions (Malamud, 2010; Lkhagvasuren, 2014) . However, UAS graduates and Swiss workers (in general) have low geographic mobility. Using graduate survey data, Pfister et al. (2021) show that 75 percent of all UAS graduates still live in the same treatment region five years after graduation.

[12] According to Sacchi (2014), the absence of online channels in the sample before 2001 does not lower its representativeness because before 2001 the majority of job ads posted online also appeared in newspapers, and the sampling process captured these ads.

To account for this gradual switch from newspaper to online job ads, and subsequent changes to how firms write job ads, we also control for the advertisement channel (i.e., newspaper, business website, or online job board).

B. *Textual Similarity with High-Skill Benchmark*

Main Results.—Figure 2 displays the estimated event study effects for vocationally trained workers, whom we expect to be affected as second-order outcomes by the establishment of UASs. First, we analyze the pretreatment effects (i.e., before the UAS graduates enter the labor market) and find no indication of upwards trends or anticipation effects in the textual similarity of job descriptions with our high-skill benchmark.[13] Second, we examine the posttreatment effects (i.e., after the first UAS graduates enter the labor market) and find a steep increase in the textual similarity of job descriptions for vocationally trained workers with the high-skill benchmark. The event study estimates show substantial upskilling effects even for middle-skilled workers without the new UAS degrees after the arrival of UAS graduates in the labor market.[14]

[Figure 2]

[13] The main identifying assumption for leveraging difference-in-differences to obtain causal estimates is that there are no systematic differences in the underlying trends of the control and treatment group. An F-Test on the pretreatment coefficients for our similarity measure outcome rejects the presence of different pretrends in the control and treatment group (p-value=0.35). Finding that job ads in regions with and without UAS campuses followed similar trends is consistent with earlier empirical results on common trends of these regions in innovation outcomes such as patent numbers and patent quality (see Pfister et al., 2021) and R&D employment patterns (as captured by the percentage of R&D personnel in firms and the labor income share of R&D workers; see Lehnert et al., 2020). Moreover, earlier studies find that the pretreatment trends in innovation outcomes hold for subgroups of regions from a wide range of economic preconditions (Schlegel et al., 2022). Relevant economic preconditions are labor market strength (i.e., total employment), labor market density (i.e., employment per hectare), and high-tech intensity (i.e., the share of high-tech employment).

[14] One question in this context is whether and, if so, how the establishment of UAS campuses affects the job openings for academic graduates (our benchmark). The empirical challenge when examining the effects on academic graduates lies in selecting an appropriate and unaffected benchmark vector for this group. To tackle this issue, we use job ads for academic graduates 10 years prior to treatment as an unaffected benchmark ("preUAS benchmark"). As a robustness check, we then examine how job ads for academic graduates in control and treatment group change afterwards compared to this benchmark. Our findings show that the establishment of UASs thus appears to not relevantly affect the skill level of job descriptions for academic graduates (see Table A1 in Appendix A).

To better assess the overall impact of the establishment of UASs, we estimate the average treatment effect by pooling the effects before and after the arrival of the new UAS graduates in a simple difference-in-differences design. Column 1 in Table 4 shows that the similarity increases by 0.019 after the opening of a nearby UAS campus. Measured by the mean similarity between vocational and academic job descriptions of 0.43 before the establishment of UASs, the effect size corresponds to a relative increase of 4.4 percent in similarity. The job descriptions for vocationally trained workers in affected regions thus became substantially more similar to those of the higher-skilled academic graduates, reflecting a positive spillover on second-order outcomes. Put differently, we observe a substantial upskilling even for those vocationally trained workers that did not acquire the new tertiary degree.

Finding upskilling of vocationally trained workers for our main specification raises the question of whether this upskilling effect reflects shifts in job content across occupations (i.e., higher skilled occupations grow or shrink) or changes of job content within occupations or industries (more or less skilled job content for the same occupation or in the same industry). To answer this question, we include (a) occupational fixed effects (at the 2-digit level of the Swiss Occupational Classification System SBN-2000) and (b) industry fixed effects (at the aggregated level of the Swiss Industry Classification system NOGA-1995) into our regression specifications. Table 4 (columns 2 and 3) shows that the magnitude of the upskilling effects is very similar in these specifications compared to our main specification without the occupation and industry fixed effects. The findings thus demonstrate that the upskilling manifests mainly within narrowly defined occupations and industries (i.e., higher skill job content for the same occupation) as opposed to manifesting across occupations and industries.

[Table 4]

Subsample Analysis.—To strengthen the causal interpretation of the upskilling effect, we proceed with subsample analyses, including a placebo test. We hypothesize that, if the arrival of UAS graduates and their positive spillovers are the sole causal drivers of upskilling, then only vocationally trained workers with links to the fields of UAS graduates (i.e., STEM) will experience upskilling after the establishment of UASs (affected subgroup), whereas those in non-STEM fields (such as health, business or social work) will remain unaffected (placebo). However, if other unobservable factors underlie our upskilling findings, we would likely also find effects for the placebo group. The subsample analyses thus enable us to examine whether the UASs are the main causal driver behind diverging control and treatment groups.

We split our sample into vocational STEM occupations with a link to the UAS campuses and vocational occupations without the STEM link. In particular, we use the Swiss Occupational Classification System (SBN2000), which helps us to identify pairs of STEM occupations at the vocational and the tertiary level. In contrast to the International Standard Classification of Occupations (ISCO), the SBN2000 classification does not separate occupations by educational levels. Instead, the SBN2000 combines academic and vocational occupations to form the same one-digit class, thereby enabling us to map vocational occupations to their academic counterpart. We pick technical and IT occupations at the one-digit level of the SBN2000 classification (SBN2000: 3) and include production workers employed in the industry and trade sectors (SBN2000: 2). These two occupational groups constitute the STEM subsample; the remainder of occupations constitutes the non-STEM subsample.

We then estimate our event study specification for the textual similarity separately for the STEM and non-STEM subsamples. Our results show that our main upskilling findings are driven by upskilling in the job descriptions of vocational STEM occupations, which have the link to the work of UAS graduates (see Figure A2, Panel A, in Appendix A). For the placebo, without that link, we find no upskilling after a new UAS campus opens up nearby (see Figure

A2, Panel B, in Appendix A). The placebo test clearly shows that the UAS graduates, not other factors drive the upskilling effects.

Alternative Benchmarks.—One potential concern with our main empirical approach is that the establishment of UASs may lead to sample selection effects across job ads for different educational levels, e.g., the presence of UAS graduates may affect the job ads of academic graduates. To tackle such concerns, we conduct three additional robustness checks: First, we take job ads for both UAS and academic graduates as one sample for the high-skill benchmark (as alternative benchmark). Second, we take job ads for academic university graduates in the 10 years before the establishment of UASs as a high-skill benchmark that is independent and unaffected by treatment (we refer to it as "preUAS benchmark"). Third, we investigate the impact of the UAS establishment on the whole sample of job ads for academic graduates, UAS graduates, and vocationally trained workers (i.e., the entire middle- and high-skill segment of the labor market) relative to the preUAS benchmark. Our results show similar empirical patterns for vocationally trained workers as in our main analysis, when we use the alternative benchmark or the preUAS benchmark (see Figure A3 and A4 in Appendix A). Examining effects for the entire middle- and high-skill segment of the labor market, we find upskilling effects that are a bit larger and our main analysis thus may even understate the true upskilling effect (see Figure A5 in Appendix A). Based on these findings, we argue that sample selection effects likely do not play a large role in our main findings.

C. *Supporting Evidence: R&D-Related Tasks as Upskilling Measure*

Given our main findings of upskilling in textual similarity, one open question is which changes in task profiles underlie these changes in textual similarity. Ideally, the increase in textual similarity towards the high-skill benchmark should be accompanied by equivalent changes in R&D-related main tasks, especially for vocationally trained workers in STEM occupations. These are tasks that best reflect the goal behind the establishment of UASs to boost innovation and prepare workers in STEM for the needs of a technology-driven economy. In particular, we examine the probability of job ads specifying R&D-related main tasks (i.e., *IT & Programming*, *Analyzing & Researching*, and *Engineering & Designing*) for vocationally trained workers. As splitting our sample into STEM and non-STEM occupations leads to smaller subsamples and R&D-related tasks (as discrete outcome variable) can be highly asymmetrically distributed across these subsamples, we pool the catchment area dummies into a single treatment group indicator to avoid issues of fragmentation.

Our results show that, after the establishment of UASs, firms substantially more often list job ads with R&D-related main tasks for vocationally trained workers in STEM (see Table A2 in Appendix A).[15] The probability of job ads mentioning R&D-related main tasks in STEM occupations increases by about 13.5 percentage points. As the SJMM data break down main tasks into 21 categories (before the establishment of UASs only 17.7 percent of the job ads belonged to the R&D-related categories), the effect of a 13.5 percentage point increase is substantial and likely explains a large fraction of the increased similarity in our text-based measure. For the placebo group, we find an insignificant treatment effect, close to zero. The findings show that firms also increasingly seek vocationally trained workers for the very same categories of main tasks (i.e., R&D-related tasks), which also the UAS graduates work in.

V. Labor Market Outcomes of Vocationally Trained Workers: Employment and Wages

As our main analysis demonstrates upskilling effects based on the job content from job ads, a consequential question is on whether and how these changes in job content translate into improvements of labor market outcomes for vocationally trained workers. In particular, we aim

[15] Firms list job ads with R&D-related main tasks not only more often at relative levels but at absolute levels (see Figure A.6 in the appendix). Moreover, we find no evidence that this addition of R&D-related main tasks for vocationally trained workers comes along with a subtraction of such tasks from academic graduates: We find no indication for a decrease in the relative frequency or absolute number of job ads for academic graduates listing R&D-related main tasks.

to answer (a) whether we also actually observe an increased employment of these workers in jobs with R&D-related tasks—as opposed to mere changes in job ads—and (b) whether we also observe wage effects for them that support the upskilling effects from the job descriptions. In the following subsections, we briefly describe our data sources and explain our approach, which is very similar to our approach for the job content (more information can be found in *Appendix B: Additional Information on the Employment and Wage Analyses*).[16] Examining employment and wage effects enables us to dig deeper into whether vocationally trained workers got elevated at the labor market level by the establishment of UASs or whether these workers got crowded out.

A. *Employment of Vocationally Trained Workers in Jobs with R&D-Related Tasks*

To investigate whether the establishment of UASs has also led to an increased employment of vocationally trained workers in jobs with R&D-related tasks, we use Swiss employer survey data. In particular, we draw on the largest representative employer survey in Switzerland (the Swiss Earnings Structure Survey, hereafter "SESS"), a repeated biennial cross section which contains rich information at both the employer and the employee level.[17] We use information on the employees' educational background to limit the sample to firms employing vocationally trained workers. Based on the main occupational activity, we identify whether vocationally trained workers conduct R&D-related tasks, i.e., whether these workers conduct "researching and developing" or "analyzing, programming, operating" (according to the SESS main task categories).[18] We then calculate the relative share of vocationally trained workers

[16] We can estimate employment and wage effects with a difference-in-differences design only for vocationally trained workers because UAS graduates or a comparable group of workers did not exist before the establishment of UASs

[17] Survey participation is mandator. The database, therefore, contains more than 35,000 firms and public administrations, and more than 1.6 million employees.

[18] The SESS contains 24 main occupational activities, of which we define—equivalent to the categories in the SJMM database—the categories "researching and developing" and "analyzing, programming, operating" as R&D-related tasks.

conducting R&D-related tasks in each firm, which gives us our outcome variable of R&D-related employment.[19]

To estimate whether firms more likely employ vocationally trained workers in jobs with R&D-related tasks after the tertiary education expansion, we again use a difference-in-differences design. Our approach and treatment definition closely follows the approach by Lehnert et al. (2020), who estimate the effects on R&D personnel by the establishment of UASs.[20] To define whether a firm is treated by the UAS campus openings and impacted by the influx of UAS graduates, we use its geographic location (for further information on treatment definition with the SESS data and common pretrends, see Appendix B). Analogous to our approach for job content, we estimate our model by using a full sample and two subsamples. As the SESS does not include information on the employees' occupation (i.e., STEM or non-STEM occupation), we have use the firm's industry sector as a proxy to define the affected subgroup. The first subsample consists of firms that are (most likely) affected by the influx of UAS graduates (manufacturing firms as a proxy for the affected STEM subgroup) and the second subsample contains firms that are assumed to be unaffected by it (non-manufacturing firms as a proxy for the non-STEM placebo subgroup).

Our results show a substantial effect for the affected (i.e., manufacturing) subgroup of firms (see Table B.1 in Appendix B): The effect of the establishment of UASs on the share vocationally trained workers employed in jobs with R&D-related tasks is about 0.31 percentage points. The effect is statistically significant at the five percent level and—given that the average share of vocationally trained workers with R&D-related tasks equals 1.8 percent in the sample of manufacturing firms—economically substantial. Furthermore we find that the effect for the placebo subsample is nonexistent. In sum, these results demonstrate that vocationally trained

[19] To consider potential bias by part-time workers, we follow Lehnert et al. (2020) and use full-time equivalents, i.e., we adjust each employee observation by its individual employment level.

[20] Lehnert et al. (2020) investigate whether the establishment of UASs led to an increase in the firms' R&D personnel. Using the Swiss Earnings Structure Survey and calculating shares of R&D personnel (relative to total employment per firm), the authors perform difference-in-differences estimations and find a statistically and economically significant increase. In contrast to Lehnert et al. (2020), we limit our sample to vocationally-trained workers to examine whether firms increase the share of these workers in jobs with R&D-related main tasks.

workers not only experience improved job opportunities but these job opportunities also translate into actual increases in high-skill employment with R&D-related tasks.

B. *Wages of Vocationally Trained Workers*

Based on this increased employment in jobs with R&D-related tasks, we further expect vocationally trained workers to receive higher wages, that is, we expect the performance of more skilled and thus better-paid tasks to lead to positive wage effects. To study wage effects by the establishment of UASs, we use the Swiss Labor Force Survey (SLFS), a representative survey from 1991 through 2008 that comprises 16,000 individuals per year until 2001, and approximately 35,000 individuals per year since 2002. The survey is particularly appropriate for our analysis because it contains information on each individual's educational background, labor market status, occupation, residence, and wage.

To construct our wage variable, we use the natural logarithm of the yearly wages. Our sample includes employed individuals of age 20 to 65[21] who work full-time[22] and have Swiss citizenship[23] and whose highest educational degree is a vocational diploma. The individuals' residence allows us to classify them as belonging to the treatment or the control group. In addition, the information on the individuals' occupations (SBN2000) allows us to distinguish between individuals affected by the establishment of UASs (STEM subsample) and a placebo subsample including workers from all remaining occupations (non-STEM subsample).

Based on difference-in-difference estimations, our results indicate that vocationally trained workers in the STEM subsample experienced a wage increase after the establishment of UASs (see Table B2 in Appendix B).[24] The treatment effect equals a 2.9 percent wage increase

[21] We thus exclude all individuals who are retired (i.e., older than 65) or in education (i.e., younger than 20 years).

[22] By using full-time equivalent wages and thereby accounting for individuals who work part-time, we find the same results as in the baseline specification.

[23] Individuals without Swiss citizenship are oversampled in the later observation period. However, the results remain unchanged if we include them.

[24] In our study, we focus on the two-thirds of the Swiss workforce that begin their educational career with vocational education and training (middle-skill segment). As the low-skill labor market segment is very small in Switzerland (only 9.8 percent of the workforce do not move

and is statistically significant at the five percent level. The average yearly wage in the affected subsample equals approximately 70,500 CHF ($70,900), and the effect of the establishment of UASs on wages (i.e., more than $2,000 per year) is thus economically sizable, too. For the placebo subsample find no wage effect. The resulting wage gains are thus unlikely an artifact of time-variant unobservable factors but instead strongly linked to the UAS campus openings. Taken together, our findings of increased R&D-related employment and higher wages show that the establishment of UASs led not only to upskilling in the job ads but also that this upskilling is linked to tangible improvements in labor market outcomes.

VI. Potential Mechanism: UAS Graduates as Bridge Builders

Which mechanism drives these effects on second-order outcomes, that is, the upskilling and improved labor market outcomes for vocationally trained workers without the new tertiary degree? We argue that the likely explanation for these effects is that UAS graduates are newly available as bridge builders between the middle-skilled vocationally trained workers and the high-skilled academic graduates.

Before the establishment of UASs, the high-skilled academic graduates (with their more abstract and fewer hands-on skills) and middle-skilled vocationally trained workers (with their more extensive occupational knowledge and hands-on experience) were far apart from one another in their competencies, professional knowledge, socialization, and occupational languages.[25] This gap made it difficult for firms to cross-fertilize the competencies of vocationally trained workers with those of academic graduates and to make effective use of the

beyond compulsory schooling; see Swiss Federal Statistical Office, 2009), we do not include it in our analyses. As the wages for workers with compulsory schooling and those with a traditional university degree steadily rose after the establishment of UASs (Swiss Federal Statistical Office, 2010), we argue that the elevation of middle-skilled workers did not come at the expense of such other skill segments.

[25] According to the organizational psychology literature, dissimilarity of team members (e.g., in their background or task understanding) decreases task performance (Gevers and Peeters, 2009), whereas overlaps and sharedness boost performance (Mathieu et al., 2000; Mohammed et al., 2010; Mohammed and Dumville, 2001; Stout et al., 1999).

professional skills of vocationally trained workers in R&D processes. We argue that the availability of UAS graduates allows for bridging this gap within firms.

UAS graduates possess the same educational and professional foundation as vocationally trained workers, who remain at their original educational level. During their studies, UAS graduates receive a tertiary education in addition to their vocational foundation and acquire applied research skills, thereby obtaining competencies that substantially overlap with those of graduates from traditional academic universities. These substantial overlaps with both academic graduates and vocationally trained workers enable UAS graduates to facilitate cooperation and communication between the two groups, increasing the overall efficiency of educationally diverse R&D teams. The bridge building enables a more efficient matching of diverse skill sets, a feature critical to R&D processes. Firms react to this increase in efficiency by increasing their R&D efforts and consequently creating additional R&D jobs, for both the UAS graduates and vocationally trained workers.

[Table 5]

Consistent with the role of UAS graduates as bridge builders, Table 5 shows that firms indeed lay great emphasis on the social and communication skills of UAS graduates. Compared to job ads for either vocationally trained workers or university graduates, job ads for UAS graduates list more words for soft skills, more often contain a communication requirement,[26] and more frequently specify *Organizing* & *Leadership* as the main task.

In this context, the question also arises as to how UAS graduates as bridge builders impact the skill demand for the group of vocationally trained workers and academic graduates (i.e., the workers on both sides of the education spectrum who are then "connected" by the UAS

[26] We consider a job ad to have a communication requirement if it contains at least one of the following keywords: "communication," "social," or "team."

graduates). On the one hand, the presence of UAS graduates may ease the need for social skills for these connected workers because bridge builders lower communication costs; on the other hand, UAS graduates may increase the amount of teamwork and thus boost the demand for social skills from the connected workers. Investigating effects on skill demand for vocationally trained workers and academic graduates (as one pooled sample), we find that job ads for the connected workers contain more words for soft skills and more often a communication requirement, which indicates more involvement in teamwork for the connected workers (see Table A3 in Appendix A). Moreover, our results suggest a negative (albeit non-significant) effect on the main task of Organizing & Leadership, which is now likely more often filled by the UAS graduates, who act as communicative bridge builders, and thus substituted away from the connected groups (see Table A3 in Appendix A).

VII. Conclusion

The question of how to prepare the workforce for new and complex jobs, especially those arising in the STEM fields and involving R&D, has attracted much attention among researchers and policymakers. In this paper, we demonstrate that the establishment of UASs—an expansion of the Swiss tertiary education system in the late 1990s—not only enabled graduates of these new institutions to advance into more skilled jobs (as first-order outcomes) but also led to an upskilling among the workers who did not acquire the new educational degree (as second-order outcomes).

For the first-order outcomes, we find that firms seek the new UAS graduates for vacancies with job descriptions textually very similar to the job descriptions for academic graduates. We show that this increased similarity is driven by a higher frequency of R&D-related main tasks, capturing that firms specifically make use of the UAS graduates' applied research skills. Graduating from a UAS thus opens up a new range of jobs, closer to those of academic graduates, and enables workers with a vocational background to climb not only the educational ladder but also the job ladder.

For the second-order outcomes, our results show certainly no signs of downskilling for vocationally trained workers who remain without the new tertiary degree. Put differently, the presence of the new, higher educated UAS graduates does not push vocationally trained workers into less attractive and less well-paid jobs with lower-skilled tasks. To the contrary, we find evidence for upskilling rather than crowding out from skilled tasks. For vocationally trained workers, firms in treated regions post job descriptions also more similar to the high-skill benchmark (4.4% more similar compared to pretreatment similarity levels). This increase in textual similarity is substantial and accompanied by an equally strong increase in R&D-related tasks (13.5 percentage point increase). Placebo tests, which show no effects for unaffected groups of workers, further support the establishment of UASs as the causal driver of these positive spillovers.

Taking together the upskilling results from our job ad analysis with our results on employment and wage effects, we conclude that the improved job opportunities for vocationally trained workers translate into tangible improvements in labor market outcomes. Despite lacking the new UAS degree, these workers are more often employed in jobs with R&D-related tasks, i.e., firms not only seek them but also actually hire them more often for such high-skill jobs. Moreover, given their higher skill tasks, these workers also experience significant wage gains. Thus, we find no evidence that the vocationally trained workers are crowded out or "squeezed out" from their well-established labor market positions but instead our results indicate that the positive job-content spillovers also manifest in positive employment and wage spillovers.

An important role for all these positive spillovers likely plays the positioning of the new tertiary education institutions in the educational landscape. The UASs are positioned to have an overlap with two traditional educational pathways: First, they overlap with vocational education and training at the middle-skill level as UAS students come from the vocational track, and, second, they overlap with education at traditional universities as UASs teach applied research, which draws from the domain of traditional academic universities. UASs are specifically designed as a new educational pathway that uses the existing strengths of vocationally trained workers and builds on these strengths to create upskilling.

Our key findings have important implications for the educational settings of other countries that also lack educational overlaps and could use existing mid-level institutions, such as polytechnical colleges in the Northern European countries or community colleges in the U.S., to better fill such gaps. Our results suggest that a tertiary education expansion with large overlaps between educational pathways and with high permeability between these paths (as implemented in the Swiss education system) can benefit workers who obtain the new degree as well as workers who remain without the new degree. The bridge-building education institution in the middle also elevates the jobs of those without the new degree, just as a rising tide lifts all boats.

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Tables & Figures

Table 1—Summary Statistics

	Obs.	Mean	Std. Dev.
Panel A. Upskilling Measure			
Cosine Similarity	8,368	0.485	0.112
Panel B. Main Tasks			
Agriculture	8,368	0.005	0.072
Manual Production	8,368	0.057	0.231
Construction & Building	8,368	0.070	0.255
Commissioning & Manually Operating	8,368	0.031	0.174
Repairing & Maintenance	8,368	0.048	0.213
Warehousing & Transport	8,368	0.012	0.108
Sales & Customer Service	8,368	0.177	0.382
Administration & Correspondence	8,368	0.165	0.371
Accounting & Finance	8,368	0.051	0.219
IT & Programming	8,368	0.050	0.217
Hospitality & Housekeeping	8,368	0.013	0.115
Cleaning	8,368	0.004	0.064
Security & Protection	8,368	0.004	0.065
Analyzing & Researching	8,368	0.041	0.199
Engineering & Designing	8,368	0.067	0.251
Recruiting & HR	8,368	0.016	0.124
Organizing & Leadership	8,368	0.102	0.303
Educating & Teaching	8,368	0.025	0.155
Legal Advising	8,368	0.000	0.015
Medical Tasks & Care	8,368	0.059	0.236
Publishing & Creative Work	8,368	0.004	0.060
Panel C. Channel			
Press	8,368	0.392	0.488
Website	8,368	0.461	0.499
Jobportal	8,368	0.147	0.354

Notes: Sample consists of job ads targeting vocationally-trained workers and job ads targeting UAS graduates. The observation period is 1995-2010. Authors' calculations with data from the Swiss Job Market Monitor.

Table 2—Correlations: Textual Similarity with High-Skill Benchmark and Main Tasks of Job Ads

	Textual Similarity
Main Tasks:	
IT & Programming	0.186***
Analyzing & Researching	0.123***
Medical Tasks & Care	0.097***
Engineering & Designing	0.094***
Educating & Teaching	0.068***
Organizing & Leadership	0.035***
Publishing & Creative Work	0.031***
Legal Advising	0.002
Hospitality & Housekeeping	-0.001
Manual Production	-0.005
Agriculture	-0.006
Recruiting & HR	-0.008
Accounting & Finance	-0.016
Security & Protection	-0.020*
Cleaning	-0.034***
Commissioning & Manually Operating	-0.038***
Repairing & Maintenance	-0.068***
Construction & Building	-0.069***
Administration & Correspondence	-0.084***
Warehousing & Transport	-0.097***
Sales & Customer Service	-0.116***

Notes: Correlations between textual similarity of job descriptions with the high-skill benchmark (i.e., job descriptions for academic graduates) and main task categories. The sample consists of job ads targeting vocationally-trained workers and job ads targeting UAS graduates. The observation period is 1995-2010. Authors' calculations with data from the Swiss Job Market Monitor. * p<0.10, ** p<0.05, *** p<0.01, respectively

Table 3—Top 10 Main Tasks of UAS Graduates

	Main Task	Relative Frequency
1.	*Organizing & Leadership*	0.256
2.	*IT & Programming*	0.181
3.	*Engineering & Designing*	0.173
4.	*Analyzing & Researching*	0.106
5.	*Educating & Teaching*	0.078
6.	*Sales & Customer Service*	0.077
7.	*Accounting & Finance*	0.050
8.	*Administration & Correspondence*	0.030
9.	*Recruiting & HR*	0.013
10.	*Publishing & Creative Work*	0.012

Notes: Mean of main task categories for UAS graduates. The sample consists of job ads targeting UAS graduates from 2000-2010. Authors' calculations with data from the Swiss Job Market Monitor.

Table 4—Effect of UAS Campus Openings on Textual Similarity with High-Skill Benchmark for Vocationally Trained Workers

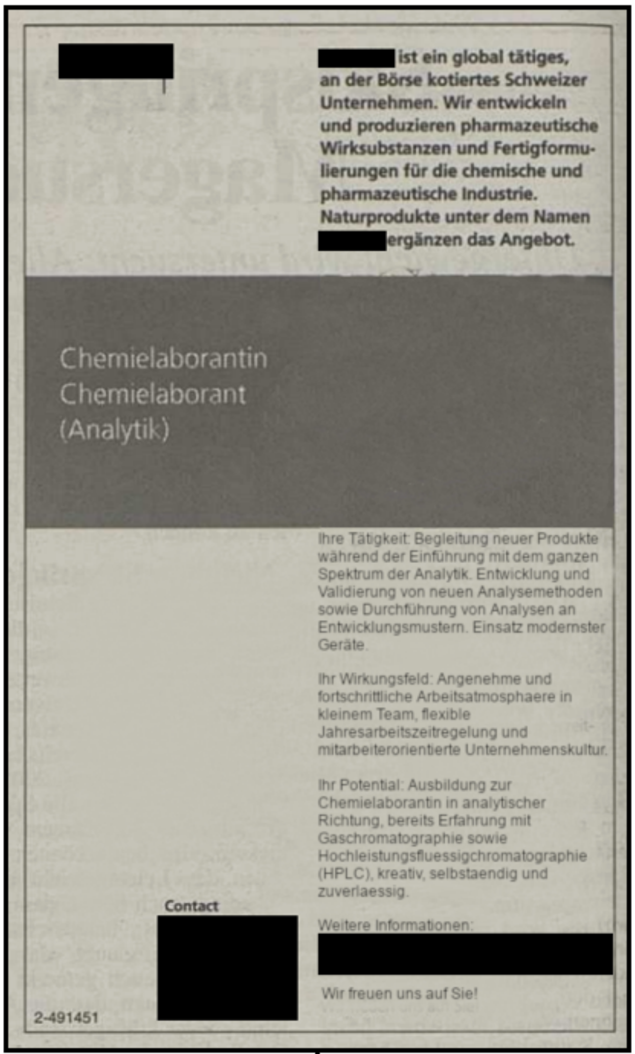
Dependent Variable	Cosine Similarity			
	(1)	(2)	(3)	(4)
Campus Opening	0.019*	0.017*	0.018*	0.052***
	(0.010)	(0.009)	(0.010)	(0.009)
Constant	0.496***	0.424***	0.481***	-1.649
	(0.012)	(0.017)	(0.013)	(1.817)
Year FE	YES	YES	YES	NO
Catchment Area FE	YES	YES	YES	YES
Channel FE	YES	YES	YES	YES
Occupation FE	NO	YES	NO	NO
Industry FE	NO	NO	YES	NO
Linear Time Trend	NO	NO	NO	YES
Observations	6,784	6,784	6,784	6,784
R-squared	0.083	0.176	0.117	0.041

Notes: Regression results from pooled difference-in-difference estimations. *Campus Opening* is an indicator capturing whether job ads actually receive the treatment from a new nearby UAS campus. *Year FE*, *Catchment Area FE,* and *Channel FE* denote including fixed effects for years, catchment areas, and advertisement channels (newspaper, company website, or online job board). *Occupation FE* refers to fixed effects at the 2-digit level of the Swiss Occupational Classification System (SBN-2000). *Industry FE* refers to fixed effects at the aggregated level of the Swiss Industry Classification system NOGA-1995. *Linear Time Trend* denotes including a parametric linear yearly time trend instead of yearly fixed effects. The sample consists of job ads from 1995-2010 targeting vocationally trained workers. Standard errors are clustered at the municipality level and reported in parentheses. Authors' calculations with data from the Swiss Job Market Monitor. Significance levels: * p<0.10, ** p<0.05, *** p<0.01, respectively.

Table 5—The Mechanism Behind the Upskilling Effects after the Establishment of UASs

	Vocationally Trained Workers		UAS Graduates		Academic Graduates		p-value of UAS Difference
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Number of Words for Soft Skills	8.010	6.834	9.537	7.161	8.251	6.846	<0.01
Communication Requirement	0.334	0.465	0.472	0.469	0.416	0.433	<0.01
Main Task: *Organizing & Leadership*	0.056	0.231	0.271	0.445	0.219	0.413	<0.01

Notes: The sample consists of job ads from 2000-2010 targeting vocationally-trained workers, UAS, or academic graduates (for better comparisons of the three groups, the preUAS years, i.e., before 2000, are excluded). P-value from t-tests for differences between (a) UAS graduates and (b) the pooled sample of vocationally trained workers and academic graduates. Authors' calculations with data from the Swiss Job Market Monitor.



[redacted]

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Contact

[redacted]

Weitere Informationen:

[redacted]

Wir freuen uns auf Sie!

2-491451

Textzone Algorithm

Firm Description (Z10)
[X] is a globally active Swiss company listed on the stock exchange. We develop and produce active pharmaceutical ingredients and finished dosage forms for the chemical and pharmaceutical industries. [X] range is completed by natural products.

Job Description (Z60)
Chemical Laboratory Technician (Analytics)
Your activity : Accompaniment of new products during their introduction with the whole spectrum of analytics. Development and validation of new analytical methods and analysis of development samples. Use of state-of-the-art equipment.

Administrative and Residual Text (Z30)
Your field of activity:

Job Description (Z60)
Pleasant and progressive working atmosphere in a small team, flexible annual working time regulation and

Firm Description (Z10)
employee-oriented corporate culture.

Administrative and Residual Text (Z30)
Your potential:

Hard Skills (Z70)
Training as a chemical laboratory assistant in the analytical field, already experience in gas chromatography and high-performance liquid chromatography (HPLC),

Soft Skills (Z80)
creative, independent and reliable.

Administrative and Residual Text (Z30)
Further information: [X]
We look forward to hearing from you !
Contact: [X]

Figure 1. Stylized Application of the Textzone Algorithm (based on Gnehm, 2018)
(*Notes:* Example for the assignment of each word to one of the eight textzones, depending on the function of the word within the text. Job ad, originally in German, translated with the DeepL web application into English for illustrative purposes.)

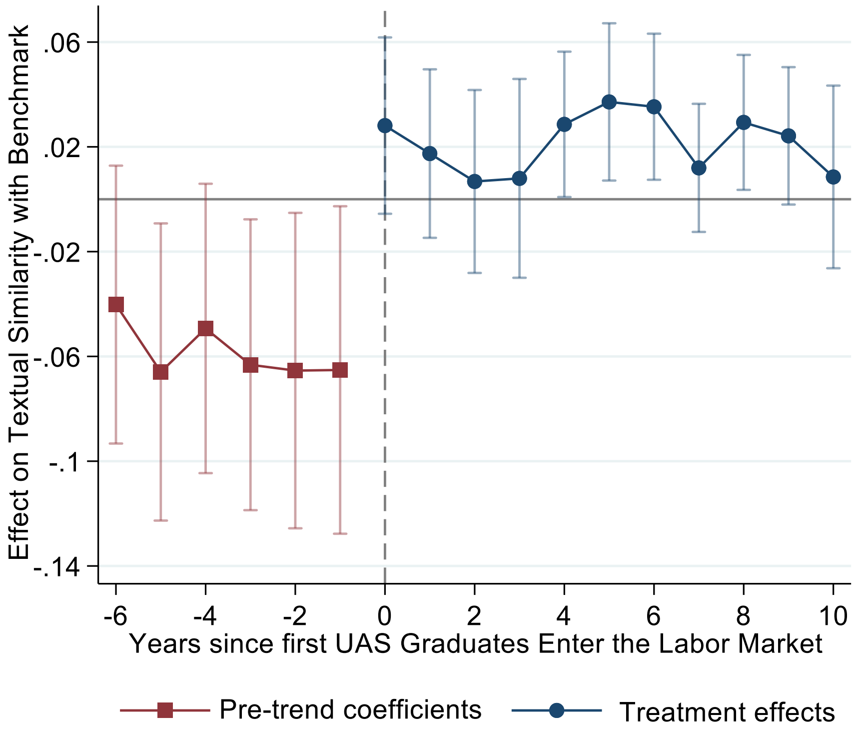

Figure 2. UAS Effect for Vocationally Trained Workers: Cosine Similarity with High-Skill Benchmark (Academic Graduates in the Same Year)

(*Notes:* Our benchmark is composed of job ads for academic graduates in a given year. Textual similarity is measured in cosine similarity with the benchmark vector based on the doc2vec algorithm. Event study estimates for vocationally trained workers based on the estimator by Borusyak et al., 2021. Standard errors are clustered at the municipality level. Confidence intervals are displayed at the five-percent level.)

Appendix A: Additional Tables & Figures

Table A1— Effect of UAS Campus Openings on Job Descriptions of Academic Graduates

Dependent Variable	Cosine Similarity
Campus Opening	0.025
	(0.036)
Constant	0.527***
	(0.046)
Year FE	YES
Catchment Area FE	YES
Channel FE	YES
Observations	1,266
R-squared	0.167

Notes: Regression results from pooled difference-in-difference estimations. The benchmark consists of job ads targeting academic graduates in the 10 years prior to the treatment (preUAS benchmark). *Campus Opening* is an indicator capturing whether job ads actually receive the treatment from a new nearby UAS campus. *Year FE*, *Catchment Area FE* and *Channel FE* denote including fixed effects for years, catchment areas and advertisement channels (newspaper, company website or online job board) respectively. The regression sample consists of job ads from 1995-2010 targeting academic graduates. Standard errors are clustered at the municipality level and reported in parentheses. Authors' calculations with data from the Swiss Job Market Monitor. * p<0.10, ** p<0.05, *** p<0.01, respectively.

Table A2—Effect of UAS Campus Openings on R&D-Related Tasks for Vocationally Trained Workers

Dependent Variable	R&D-Related Main Task	
	(1) STEM Subsample	(2) Non-STEM Subsample
Campus Opening	0.135***	-0.004
	(0.035)	(0.010)
UAS-Mun.	0.007	0.004
	(0.039)	(0.009)
Constant	0.320***	-0.003
	(0.083)	(0.007)
Year FE	YES	YES
Channel FE	YES	YES
Observations	1,906	4,878
R-squared	0.072	0.009

Notes: Regression results from pooled difference-in-difference estimations. The dependent variable is an indicator capturing whether a job ad specifies "IT & programming," "analyzing & researching," and "engineering & designing" as main task. *Campus Opening* is an indicator capturing whether job ads actually receive the treatment from a new nearby UAS campus. To avoid issues of fragmentation in small subsamples and with too many fixed effects, we pool catchment area fixed effects into a single indicator depending on treatment status. *UAS-Mun.* is an indicator capturing whether job ads are from municipalities that eventually receive a UAS campus. *Year FE* and *Channel FE* denote including fixed effects for years and advertisement channels (newspaper, company website or online job board). We estimate a linear probability model. The sample consists of job ads from 1995-2010 targeting vocationally trained workers. We separate STEM from non-STEM occupations. Standard errors are clustered at the municipality level and reported in parentheses. Authors' calculations with data from the Swiss Job Market Monitor. * $p<0.10$, ** $p<0.05$, *** $p<0.01$, respectively.

Table A3— Effect of UAS Campus Openings on Social-Skill and Communication Requirements of Vocationally Trained Workers and Academic Graduates

Dependent Variable	(1) Number of Soft-Skill Words	(2) Communication Requirement	(3) Main Task: *Organizing & Leadership*
Campus Opening	1.693**	0.068*	-0.029
	(0.821)	(0.037)	(0.023)
Constant	4.227***	0.174***	0.008
	(0.706)	(0.044)	(0.021)
Year FE	YES	YES	YES
Catchment Area FE	YES	YES	YES
Channel FE	YES	YES	YES
Observations	9,013	9,013	9,013
R-squared	0.117	0.054	0.023

Notes: Regression results from pooled difference-in-difference estimations. Outcomes are *Number of Soft-Skill Words* (measured by the number of soft skill words in a job ad), and *Communication Requirement* (measured by whether at least one keyword of "communication," "social," or "team" appears in a job ad), *Main Task: Organizing & Leadership* (measured by whether a job ad has *Organizing & Leadership* as its main task). *Campus Opening* is an indicator capturing whether job ads actually receive the treatment from a new nearby UAS campus. *Year FE*, *Catchment Area FE,* and *Channel FE* denote including fixed effects for years, catchment areas and advertisement channels (newspaper, company website or online job board). The sample consists of job ads from 1995-2010 targeting vocationally trained workers or academic graduates. Standard errors are clustered at the municipality level and reported in parentheses. Authors' calculations with data from the Swiss Job Market Monitor. Significance levels: * p<0.10, ** p<0.05, *** p<0.01, respectively.

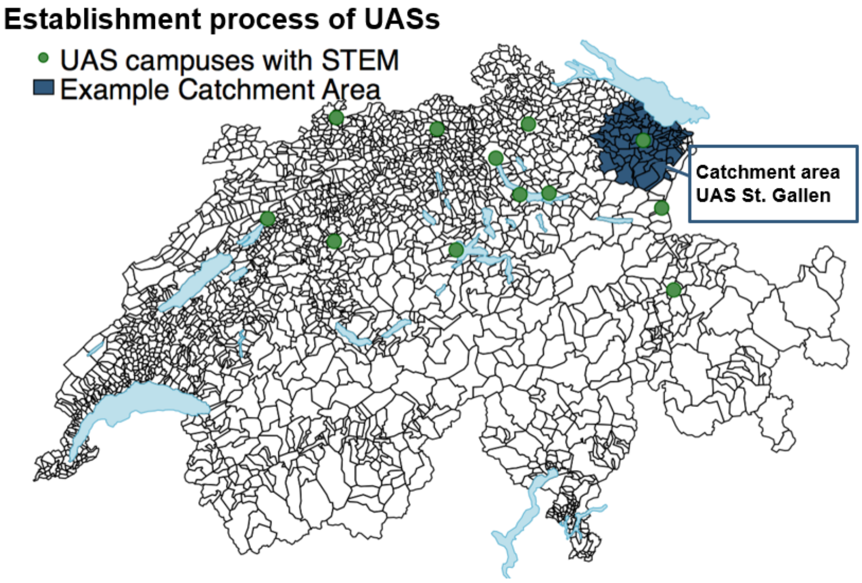

Figure A1: Geographic Location of UAS campuses with STEM fields and Example of Catchment Area (based on Pfister et al., 2021)
(*Notes:* Locations of UAS campuses in STEM. Example of catchment area for Campus St. Gallen of the "Ostschweizer Fachhochschule")

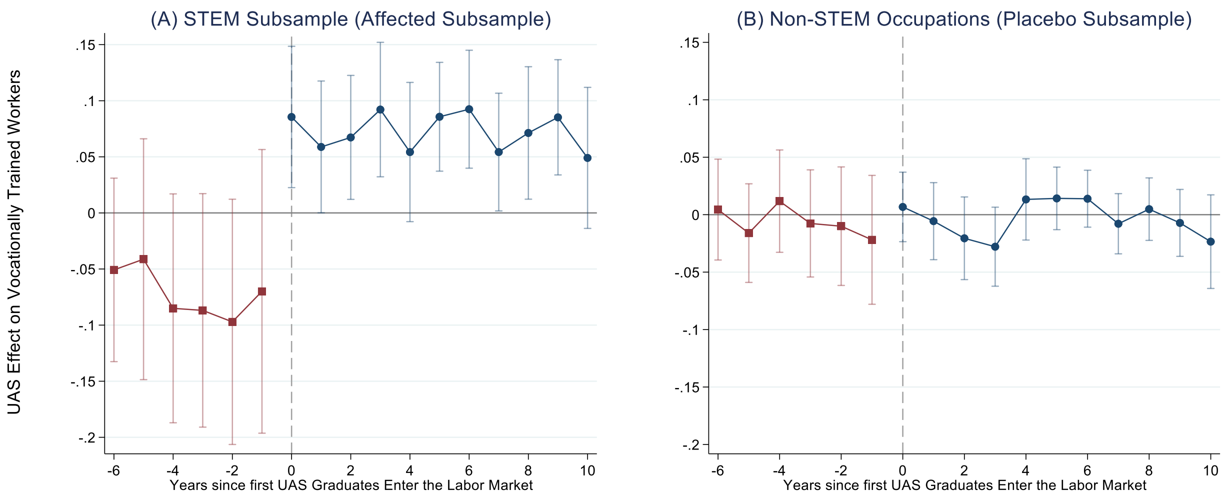

Figure A2. UAS Effect for Vocationally Trained Workers: Cosine Similarity with High-Skill Benchmark (STEM versus Non-STEM)
(*Notes:* Event study estimates for vocationally trained workers based on the estimator by Borusyak et al., 2021. The STEM subsample consists of job ads for vocationally trained workers in technical and IT occupations and production occupations in the industry and trade sectors. The non-STEM subsample consists of the remainder of occupations for vocationally trained workers, e.g., in health, business, or social work. Standard errors are clustered at the municipality level. Confidence intervals are displayed at the five-percent level.)

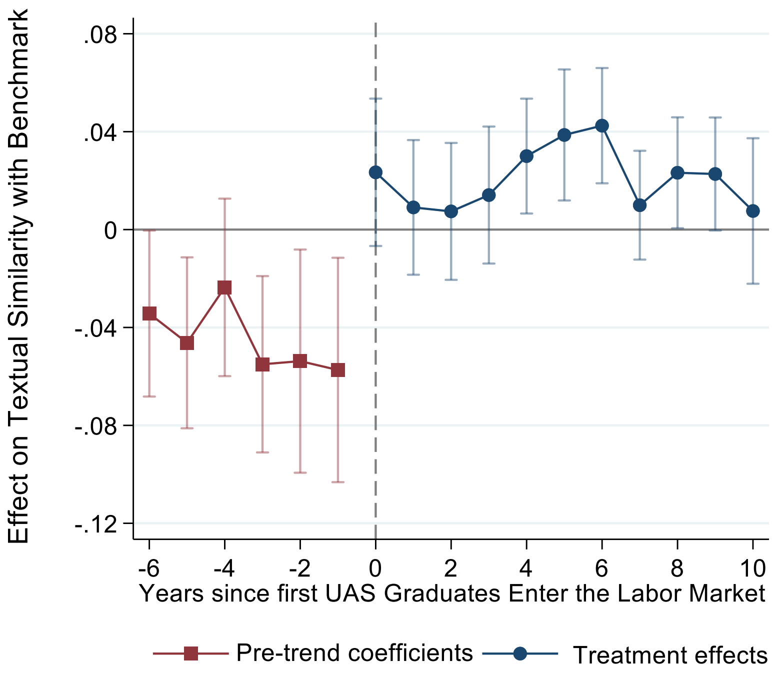

Figure A3. Effect on Textual Similarity for Vocationally Trained Workers with Alternative High-Skill Benchmark (Job Ads for UAS and Academic Graduates)
(*Notes:* The alternative benchmark is composed of job ads for all high-skill jobs, i.e., both UAS and academic graduates in a given year. Similarity is measured in cosine similarity with the benchmark vector based on the doc2vec algorithm. Event study estimates for vocationally trained workers based on the estimator by Borusyak et al., 2021. Standard errors are clustered at the municipality level. Confidence intervals are displayed at the five-percent level.)

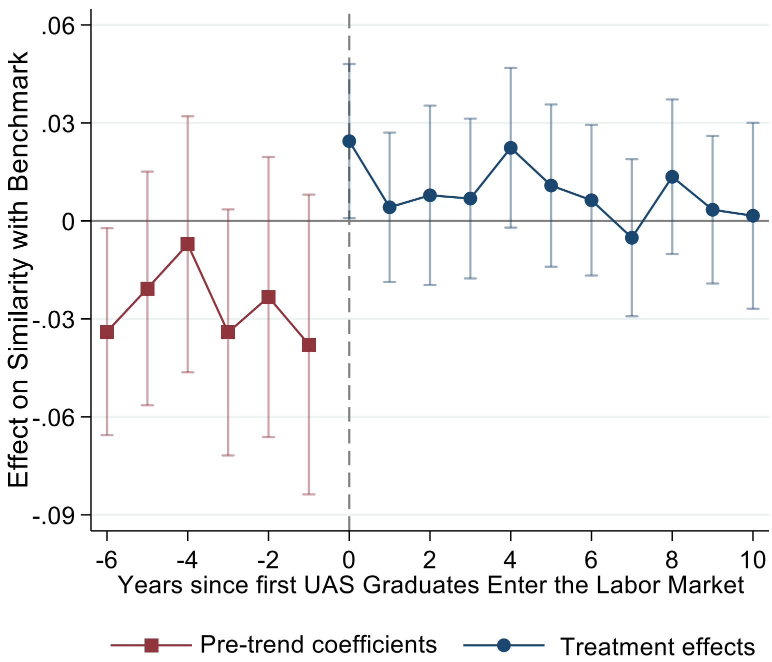

Figure A4. Effect on Textual Similarity for Vocationally Trained Workers with preUAS Benchmark
(*Notes:* The preUAS benchmark is composed of job ads for academic graduates in the 10 years before the establishment of UASs. Similarity measured in cosine similarity with the benchmark vector based on the doc2vec

algorithm. Event study estimates for vocationally trained workers based on the estimator by Borusyak et al., 2021. Standard errors are clustered at the municipality level. Confidence intervals are displayed at the five-percent level.)

Figure A5. Effect on Textual Similarity for Vocationally Trained Workers, UAS graduates, and Academic Graduates with preUAS Benchmark

(*Notes:* The preUAS benchmark is composed of job ads for academic graduates in the 10 years before the establishment of UASs. Similarity measured in cosine similarity with the benchmark vector based on the doc2vec algorithm. Event study estimates with full sample of job ads for academic graduates, UAS graduates, and vocationally trained workers based on the estimator by Borusyak et al., 2021. Standard errors are clustered at the municipality level. Confidence intervals are displayed at the five-percent level.)

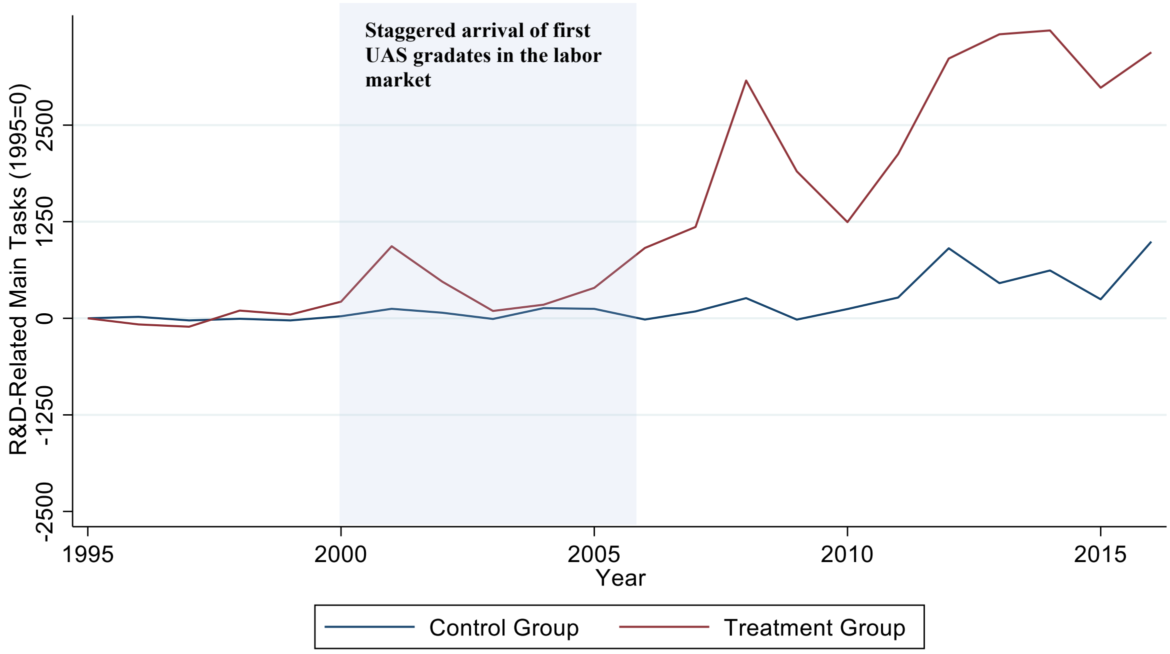

Figure A6. Raw Trends in Total Number of Job Ads with R&D-Related Main Tasks in Treatment and Control Group

(*Notes:* The sample consists of job ads for vocationally trained workers in STEM, i.e., job ads for technical and IT occupations and production occupations in the industry and trade sectors. The initial level in both the regions with and without a UAS campus is set to 0, so that the curves of both groups are shifted to the same initial level.)

Appendix B: Additional Information on the Employment and Wage Analyses

In the section on *V. Labor Market Outcomes of Vocationally Trained Workers: Employment and Wages* in the main text, we presented evidence from two additional data sources. This appendix section provides the result tables, additional information on the treatment definition with the data from the Swiss Earnings Structure Survey (SESS), and on common trends in both employment and wages.

Table B1—The Effects of the UAS Campus Openings on R&D Employment

Dependent Variable:	Share of vocationally trained workers in R&D					
	Full Sample		Manufacturing Sample		Nonmanufacturing Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Campus Opening	0.0014	0.0006	0.0026*	0.0031**	0.0009	-0.0000
	(0.0011)	(0.0011)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
UAS-Mun.	0.0099***	0.0026**	0.0047***	-0.0000	0.0116***	0.0035***
	(0.0010)	(0.0010)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Constant	0.0090***	0.0086***	0.0120***	0.0032*	0.0079***	0.0110***
	(0.0011)	(0.0013)	(0.0015)	(0.0019)	(0.0015)	(0.0017)
Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	NO	YES	NO	YES
Observations	151,197	151,197	41,947	41,947	109,250	109,250
R^2	0.0056	0.1115	0.0024	0.0737	0.0067	0.1172

Notes: *Campus Opening* denotes whether firms j in year t receives the treatment from a UAS campus opening. *UAS-Mun.* indicates whether firm j is located in a MS region that will be eventually fully treated by a UAS campus opening (treatment group fixed effect). *Year FE* refers to a set of yearly indicators. Control variables at the level of stratification include canton fixed effects, dummies for firm size (the first category involves firms with less than 20 employees, second category firms with 20 to 49 employees, third category firms with more than 50 employees) and dummies for the industry sector (two-digit NOGA). Authors' calculations, based on SESS. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level, respectively.

Table B2—The Effects of UAS Campus Openings on Wages

Dependent variable:	ln(wages)		
	Full Sample	Subsample: STEM occupations	Placebo: Non-STEM occupations
	(1)	(2)	(3)
Campus Opening	0.0124	0.0292**	0.0032
	(0.0077)	(0.0114)	(0.0098)
UAS-Mun.	0.0169**	-0.0098	0.0283***
	(0.0078)	(0.0113)	(0.0100)
Constant	10.8646***	10.9254***	10.8379***
	(0.0135)	(0.0203)	(0.0172)
Year FE	YES	YES	YES
Controls	YES	YES	YES
Observations	49,209	14,255	34,954
R^2	0.0480	0.0659	0.0455

Notes: *Campus Opening* denotes whether an individual in a given year receives the treatment from a UAS campus opening. *UAS-Mun.* indicates whether an individual lives in a municipality that will be treated by a UAS campus opening (treatment group fixed effect). *Year FE* refers to a set of yearly indicators. *Controls* include individual controls such as age and tenure and cantonal indicators to control for canton-specific labor market regimes (e.g., different taxation). Authors` calculations, based on SLFS. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level, respectively.

Treatment Definition in the SESS.—To define whether a firm in the SESS is treated by the UAS campuses and the influx of UAS graduates, we use its geographic location. However, the SESS provides us with information on the firm's location only at the level of "mobilité spatiale" (MS) regions, not at the more granular level of municipalities (which we used to define treatment status in our main analysis on job content).[27] The number of these MS regions equals 106 and their aggregation level therefore resides between the level of cantons (26 cantons) and

[27] These MS regions are designed for regional-political or scientific purposes, constituting micro-regional areas that are characterized by spatial homogeneity and that represent small labor markets (Schuler et al. 2005). For further information, see https://www.bfs.admin.ch/bfs/de/home/statistiken/raum-umwelt/nomenklaturen/msreg.assetdetail.415729.html

the level of municipalities (approximately 2,300). We are therefore not able to define the exact borders of the treated area and have to take an alternative approach.

We follow Lehnert et al. (2020) and define the intensity (the dosage of the treatment) using census data on the distribution of the treated population in each MS region. For each MS region, we add up the number of individuals living in the treated region and calculate the share relative to the entire population in the MS region. This share shows the dosage of the treatment for the MS region. We classify regions that are fully treated (100 percent) to the treatment group; regions that are not fully treated (99 percent or less) constitute the control group, implying that we estimate a lower bound of the effect.

Common Trend in Employment and Wages.—The main identifying assumption for a difference-in-difference approach is that control and treatment groups would have continued to follow a common trend, absent of treatment. Pretreatment trends give a good indication whether this common trend assumption holds. For employment (in job with R&D-related tasks) as our first labor market outcome, Table B3 shows that firms in the treatment and control groups follow common trends in the full sample and the two subsamples for manufacturing and nonmanufacturing firms. For wages as our second labor market outcome, we also no indication for a violation (see, Table B4). Taken together, we thus find no indication for a violation of the common trends assumption for both our labor market outcomes.

Table B3—Common Trends in R&D Employment Across Treatment and Control Regions

Dependent Variable:	Share of vocationally trained workers in R&D					
	Full Sample		Manufacturing Sample		Nonmanufacturing Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
UAS-Mun.	0.0070***	-0.0013	0.0018	-0.0021	0.0096***	-0.0012
	(0.0019)	(0.0020)	(0.0028)	(0.0028)	(0.0025)	(0.0026)
1996* UAS-Mun.	0.0029	0.0030	0.0056	0.0056	0.0007	0.0023
	(0.0032)	(0.0030)	(0.0042)	(0.0040)	(0.0041)	(0.0038)
1998* UAS-Mun.	0.0070**	0.0053*	0.0014	-0.0005	0.0075*	0.0073**
	(0.0032)	(0.0030)	(0.0051)	(0.0049)	(0.0039)	(0.0037)
2000* UAS-Mun.	0.0019	0.0025	0.0028	0.0030	0.0002	0.0021
	(0.0038)	(0.0035)	(0.0057)	(0.0054)	(0.0048)	(0.0044)
Constant	0.0108***	0.0085***	0.0138***	0.0072*	0.0092***	0.0094***
	(0.0013)	(0.0023)	(0.0020)	(0.0038)	(0.0017)	(0.0029)
Controls	NO	YES	NO	YES	NO	YES
Observations	22,055	22,055	5,618	5,618	16,437	16,437
R^2	0.0037	0.1304	0.0025	0.0874	0.0041	0.1378

Notes: *UAS-Mun.* indicates whether a firm is located in a MS region that will be eventually fully treated by a UAS campus opening (treatment group fixed effect). Control variables at the level of stratification include canton fixed effects, dummies for firm size (the first category involves firms with less than 20 employees, second category firms with 20 to 49 employees, third category firms with more than 50 employees) and dummies for the industry sector (two-digit NOGA). Authors' calculations, based on SESS. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level, respectively.

Table B4—Common Trend in Wages Across Treatment and Control Regions

Dependent variable:	ln(wages)		
	Full Sample	Subsample: STEM occupations	Placebo: Non-STEM occupations
	(1)	(2)	(3)
UAS-Mun.	0.0302	0.0067	0.0396
	(0.0320)	(0.0516)	(0.0402)
1992* UAS-Mun.	0.0214	0.0022	0.0332
	(0.0434)	(0.0638)	(0.0548)
1993* UAS-Mun.	0.0346	0.0652	0.0219
	(0.0443)	(0.0620)	(0.0583)
1994* UAS-Mun.	0.0100	0.0227	0.0043
	(0.0373)	(0.0619)	(0.0461)
1995* UAS-Mun.	0.0142	0.0385	0.0039
	(0.0370)	(0.0560)	(0.0489)
1996* UAS-Mun.	0.0741*	0.0759	0.0761
	(0.0388)	(0.0641)	(0.0500)
1997* UAS-Mun.	0.0563	0.0398	0.0701
	(0.0393)	(0.0572)	(0.0493)
1998* UAS-Mun.	0.0208	0.0041	0.0340
	(0.0367)	(0.0604)	(0.0442)
1999* UAS-Mun.	0.0312	0.0051	0.0441
	(0.0382)	(0.0599)	(0.0471)
2000* UAS-Mun.	0.0210	0.0171	0.0238
	(0.0404)	(0.0568)	(0.0509)
Constant	10.8592***	10.9191***	10.8339***
	(0.0281)	(0.0480)	(0.0344)
Observations	22,905	6,567	16,338
R^2	0.0213	0.0267	0.0209

Notes: *UAS-Mun.* indicates whether an individual lives in a municipality that will be treated by a UAS campus opening (treatment group fixed effect). Authors' calculations, based on SLFS. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level, respectively.

Appendix C: Examples of Job Ads and their Textual Similarity with the High-Skill Benchmark (Selected from the 3rd and the 97th Percentile in Similarity)

1. High Textual Similarity

Similarity with high-skill benchmark = 0.79
Executive Assistant: Do you relish a challenge? Are you looking for a new outlook in your professional life that will allow you to develop further? As a global leader in risk and capital management our success is built on forward-looking committed employees who are keenly focused on quality. Are you ready for the challenge?

Your Job: We are looking for an assistant to the Head Corporate Technology and the team leaders, providing professional and pro-active support. You will manage the diary of the Department Head and handle all correspondence, prioritizing, responding, delegating, and taking appropriate action in the absence of the Department Head. You will also deal with various reporting and administrative duties including planning travel itineraries; arranging meetings, conferences, and events; and screening incoming telephone calls and e-mails. Furthermore you will be the department's Time Manager
.
Desired employment percentage: 100 %

Your Profile: - flexible, reliable, trustworthy, service-oriented - independent working style - strong communication, planning, presentation, and writing skills - sound commercial background - at least 2 years professional experience in a comparable assistant function - good knowledge of English and German (spoken and written) - good skills in MS Office (in particular Power Point and Excel)

Similarity with high-skill benchmark = 0.76
Informatics BARANDUN Engineering Innovative Solutions

We are a company for customized IT solutions, which is active throughout Switzerland. To complement our customer-oriented technical team, we are looking for a dedicated informatics specialist or technician for the planning, conception, and realization of network projects based on Windows and Linux technology.

You have an informatics or technician vocational diploma and very good knowledge on Windows Server and Client Exchange Server as well as Linux.

Your strengths are teamwork and commitment, an independent way of working, flexibility and the ability to work under pressure.

Have we sparked your interest?

Then we look forward to receiving your application: BARANDUN Engineering AG

Similarity with high-skill benchmark = 0.75
IT Project Manager Analyst

With a commercial or technical training diploma, several years of experience in software development and implementation, preferably knowledge of IBM AS 400 and command of the English language, you fulfill the requirements for the responsible tasks as IT Project Manager/Analyst.

The tasks include: project management, specifications of software adjustments as well as the implementation of standard IT solutions and individual IT solutions in logistics applications and sales applications.

If you are a self-starter and an enthusiastic and responsible person with the ability to work under pressure and in a team, we hope we have sparked your interest. We look forward to receiving your written application.

2. Low Textual Similarity

Similarity with high-skill benchmark = 0.05

SWISS CHOCOLATIER

To strengthen our team we are looking for: Confiserie salesperson/Auxiliary salesperson If you have a completed vocational training or possess industry experience and good German and English skills, are flexible and motivated, then we look forward to meeting you!

Send your written application with photo to: [X]

Similarity with high-skill benchmark = 0.16

For our team we are looking for a dynamic independent employee (mobile crane) with driver's license Category C and E.

Responsibilities: Transport and crane work (mobile crane), maintenance of vehicles and machinery

Do you like to work independently and reliably? Then you can realize your ideas and take the initiative with us and our customers.

We offer modern employment conditions. If these varied and responsible tasks correspond to your wishes and abilities, we look forward to getting to know you. Please send your application in writing to: [X].

Similarity with high-skill benchmark = 0.22

TECHNOMAG

You want more... With your skills you contribute directly to the success of our team. As a skilled and motivated repair shop employee you are interested in diversified work and also willing to take over the responsibility for our branch repair shop.

We are specialized in the revision of brakes and clutches for cars and commercial vehicles. You will also be employed as a driver (driving license category B) for delivery to our garage customers. There you can prove your sales talent daily.

We will support you in your new job with a thorough introduction. Thanks to our unique concept, we are the leader in Switzerland in the car parts service. We look forward to getting to know you.

Please send your written application to our branch manager: [X]