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Employment of R&D personnel after an educational supply shock: Effects of the introduction of Universities of Applied Sciences in Switzerland*

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Abstract

We examine whether firms increase their employment of R&D personnel in response to an expansion of tertiary education institutions, i.e., a supply shock of skilled labor. We use the staggered introduction of Universities of Applied Sciences (UASs) in Switzerland as a quasi-natural experiment to identify causal effects. Firms located near a new UAS campus experience an education-driven labor supply shock in the form of UAS graduates newly entering the local labor market. Using a large representative firm survey and applying a difference-in-differences model, we find that this labor supply shock has positive effects: first, on the percentage of R&D personnel relative to total employment and, second, on the percentage of total wages paid to them. These effects are driven by both very small firms (five to nine employees) and very large ones (5,000 or more). Our findings suggest that a tertiary education expansion can stimulate innovation activities by increasing the personnel resources devoted to R&D.

Keywords: R&D personnel, applied research, tertiary education expansion, Switzerland

JEL Classification Numbers: I23, I28, J24, O31, O32

1. Introduction

A tertiary-level education expansion creates a supply shock of graduates with R&D-specific skills in the labor market, giving firms easier and more opportunities to hire graduates for their R&D departments. Therefore, governments often expand tertiary-level education institutions to increase innovation and competitiveness through providing more future workers with the skills necessary for R&D activities (Organization for Economic Co-operation and Development (OECD), 2010, 2017). However, causal empirical evidence on the employment effects of tertiary education expansions is rare, particularly on how firms respond in terms of employing R&D personnel. Thus investigating whether and, if so, to what extent firms make use of workers with new R&D skills is very important. More specifically, analyzing whether firms employ more R&D personnel and increase overall spending on R&D personnel (as wages) is crucial.

This paper analyzes how the educational supply shock resulting from the introduction of a particular type of tertiary education institution—Universities of Applied Sciences (UASs), which recruit their students from vocational apprenticeship graduates and which both teach and conduct applied research—has affected firms' employment in R&D in Switzerland. The government introduced UASs to provide graduates from dual apprenticeship programs (i.e., upper-secondary-level vocational education) with an educational upgrade to the tertiary level (Swiss Coordination Centre for Research in Education (SCCRE), 2018). Therefore, students at UASs are not comparable to students at other tertiary education institutions, because UAS students already have a sound vocational knowledge base through their secondary-level vocational education. By obtaining a UAS degree, these students attain more advanced vocational and professional knowledge combined with applied research skills, often using them for, and in close cooperation with, local firms. Therefore, we expect the introduction of UASs to have different effects on firms' R&D than the introduction of academic universities, which generally recruit their students from high school graduates. Due to the UASs' close combination of a strong practical vocational knowledge base with applied research skills, we expect substantial effects on R&D and innovation, particularly in firms or regions that did not previously have a strong tradition of innovation.

To identify the causal effect of the introduction of UASs, we exploit a quasi-random variation in the location and timing of the openings of UAS campuses in Switzerland in the 1990s. In so doing, we follow a growing literature that uses the openings of new tertiary education institutions as an identification strategy (e.g., Jäger, 2013; Kamhöfer et al., 2019; Kyui, 2016; Pfister et al., 2018; Toivanen and Väänänen, 2016). We apply a difference-in-differences (DiD) design to compare the employment of R&D personnel in treated firms (i.e., firms in labor market regions where a UAS campus has opened) to the employment of R&D personnel in untreated firms (i.e., firms in labor market regions where no UAS campus has opened).

For our analysis, we draw on repeated cross-sectional data from the Swiss Earnings Structure Survey (ESS). This data allows us (a) to observe firms at the establishment level (i.e., at their different locations), which we need to identify treated and untreated locations, and (b) to precisely measure firms' R&D personnel by providing information on the job tasks of individual workers and, in turn, on firms' direct labor input dedicated to innovation activities. Through these unique ESS data features, we can investigate how the labor supply shock resulting from the introduction of UASs affects the employment of R&D personnel (measured as the percentage of a firm's personnel with R&D tasks as their main job activity). Moreover, we can also investigate the effect on wages paid to R&D employees (measured as the percentage of the total wage sum paid to personnel with R&D tasks as their main job activity) in treated establishments in comparison to untreated establishments.

Our analysis shows that firms affected by the opening of a UAS campus employ more R&D personnel and spend more money on R&D personnel, clearly engaging more intensively in R&D. This finding implies that firms located near a UAS campus use the R&D skills available in the labor market after the opening of the campus. Furthermore, we study whether these effects are heterogeneous across different types of firms and find that both very small firms (with 5–9 employees—and thus possibly start-ups) and very large firms (with 5,000 or more employees) profit from the introduction of UASs. These results show that an education expansion providing individuals with relevant practical skills in applied R&D can stimulate firms' innovation activities. Particularly for small firms, the skills of UAS graduates constitute a valuable resource, enabling these firms to engage in or intensify their R&D activities.

This paper contributes to three strands of the literature on how the skills available in local labor markets influence firms' innovation activities. First, we contribute to the literature on the innovation effects of tertiary education institutions (which produce skills for local labor markets) by providing evidence on the innovation effect of introducing a new tertiary education institution that—compared to an academic university—teaches different types of skills to graduates of different types of secondary education. Despite numerous studies on the effect of academic universities on innovation (e.g., Audretsch and Feldman, 1996; Cowan and Zinovyeva, 2013; Jaffe, 1989), no evidence exists on the effect of the structurally very different UASs—tertiary education institutions teaching graduates from dual apprenticeship programs and focusing on vocational and applied research knowledge—on innovation activities.

Studies investigating the innovation effect of traditional academic universities, which teach high school graduates and focus on theoretical knowledge and basic research, confirm that firms gain from academic universities and that these spillovers are concentrated in firms close to an academic university (e.g., Andersson et al., 2009; Anselin et al., 1997; Autant-Bernard, 2001). Moreover, studies examining the innovation effect of academic universities focusing on technical knowledge in science, technology, engineering, and mathematics (STEM)—universities that still teach graduates from high-school programs and that do not focus on vocational and applied research knowledge—show that these institutions raise, for example, the propensity for graduates to become inventors (Bianchi and Giorcelli, 2019; Toivanen and Väänänen, 2016). In addition, studies on the openings of U.S. colleges, some of which teach and conduct applied research but primarily to high school graduates, also show positive innovation effects (Andrews, 2019; Moretti, 2004).

Nonetheless, all these tertiary education institutions structurally differ from the UASs we analyze in this paper. Although some of these institutions teach a certain amount of applied or STEM-related skills, they do not focus on students who are graduates from dual apprenticeship programs and who already have a solid practical vocational knowledge base from their three- to four-year education, which includes an apprenticeship in firms. Thus we specifically analyze the effects of the close combination of solid practical vocational skills from a dual apprenticeship program with applied research skills. Such a combination might have particularly sizable effects on R&D intensity and innovation in firms or regions that did not previously have a strong tradition of innovation.

Second, we add to the literature that examines the importance of vocational skills for innovation activities by demonstrating that augmenting the skill base of vocationally trained workers with applied research skills contributes to innovation activities in firms that have access to the new type of graduates. Only few studies show that secondary-level vocational skills (i.e., those of graduates from dual apprenticeship programs) positively affect innovation in firms (e.g., Meuer et al., 2015; Rupietta and Backes-Gellner, 2019; Toner, 2010). Moreover, Cinnirella and Streb (2017), who study 19$^{\text{th}}$-century Prussia, identify the knowledge of "master craftsmen" (a form of advanced skills in a specific occupation) as an important driver of technological development in that century. Our paper extends these findings by providing first evidence that augmenting secondary-level vocational skills (which UAS students alreay have from their dual apprenticeship training) with tertiary-level applied research skills has additional effects on firms' innovation activities, as measured by an increase in R&D employment and intensity.

Third, we extend the literature that assesses the innovation effect of tertiary education expansions (e.g., Cowan and Zinovyeva, 2013; Leten et al., 2014; Toivanen and Väänänen, 2016) by directly showing that firms' use of the newly available skills for their R&D activities constitutes one mechanism underlying the innovation effect of tertiary education expansions. While Pfister et al. (2018) find that the introduction of UASs in Switzerland increases innovation outcomes (as measured by patenting activities), we show that firms' employing UAS graduates as an input for their R&D activities is a potential driver of the increase in innovation outcomes. Moreover, our results show that the particular skill combination of UAS graduates (sound practical vocational knowledge and applied research skills) forms an important missing link between vocationally trained middle-skilled workers in production and academically trained workers in R&D. Their presence helps increase innovation capabilities through a more effective combination of different types of knowledge and, consequently, more creative solutions to innovation problems (Backes-Gellner and Pfister, 2019; Schultheiss et al., 2019).

The paper proceeds as follows: Section 2 explains the institutional background of the introduction of UASs in Switzerland and hypothesizes how the resulting supply shock of skilled labor may influence firms' R&D. Section 3 describes our ESS data and our measures of R&D personnel. Section 4 presents and discusses our DiD approach to identify the treatment effect. Section 5 reports the main results and further assesses whether the treatment effect is heterogeneous across different types of firms. Section 6 concludes.

2. Institutional background

2.1. UASs and the vocational and applied research skills of their graduates

In comparison to academic university graduates, UAS graduates possess a very distinct and unique set of vocational and applied research skills. This distinction results from the legal mandates of UASs within the Swiss education system. This system consists of both a vocational and an academic pillar at the tertiary level (according to the International Standard Classification of Education (ISCED)). About 70 percent of students who complete compulsory schooling opt for a vocational track by starting some form of vocational education and training (VET), usually a dual apprenticeship program.[1] An apprenticeship program includes practical on-the-job training in host firms (about 80 percent of the time) and theoretical teaching in vocational schools (about 20 percent), with both parts adhering to well-defined curricula. Graduates receive a nationally recognized VET certificate.[2] Until the 1990s reform, VET students had no direct career path to a university education, as

[1] See https://www.bfs.admin.ch/bfs/en/home/statistics/education-science/diploma/upper-secondary.html (last retrieved on April 16, 2019).

[2] See, e.g., Backes-Gellner et al. (2017) or Eggenberger et al. (2018) for a short description of the economically important aspects of the Swiss VET system.

academic universities accepted only students from the academic (i.e., non-VET) education track. The goal of creating the UASs was to provide an equivalent—yet different—educational path for VET graduates.[3]

After the 1990s reform, dual VET graduates who acquired a professional baccalaureate (*Berufsmaturität*)—a degree that supplements the VET degree and requires additional courses and exams—had the new option of entering a UAS. While studying at a UAS, these dual VET graduates accumulate a combination of advanced occupational knowledge and applied research skills. Thus UAS graduates possess two types of skills: First, they have a solid vocational skill set within their occupation (from, e.g., a four-year apprenticeship training as a laboratory technician or a three-year apprenticeship training as a mechanic). Second, through their UAS education, they have enhanced their original skill set and acquired new applied research knowledge in their occupational field. Their skill set thus differs from that of academic university graduates, who have acquired more theoretical and basic research skills, not practical *vocational* and *applied* research skills.

This difference in the skill profiles of UAS graduates and academic university graduates results from the strict separation of the academic and vocational tracks in the Swiss education system. The selection mechanism determining eligibility for a UAS ensures that the skills of UAS graduates differ from those of academic university graduates (for an overview of transitions from secondary to tertiary education in Switzerland, see SCCRE, 2018). After completing their secondary-level education, students in the academic track can easily proceed to an academic university and students in the vocational track (with a professional baccalaureate) can easily proceed to a UAS. Although theoretically possible (i.e., if students fulfill certain additional requirements after completing secondary education), very few students transfer from the academic to the vocational track, or vice versa. Through this design feature of the Swiss education system, students at UASs have a strong vocational knowledge base to build upon, and UASs add applied research skills.

[3] In addition to giving VET graduates a formal education equivalent to that of academic universities, UASs are legally required to apply scientific methods and knowledge in their teaching and research, to provide services to public or private sector firms, and to collaborate with firms and other research institutions. For further information on UASs and their legal mandates, see Projektgruppe Bund–Kantone Hochschullandschaft 2008 (2004) or State Secretariat for Education, Research and Innovation (SERI) (2015).

The field of electrical engineering offers a clear illustration of the differences between a UAS graduate and an academic university graduate. An academic university graduate with a degree in electrical engineering would, for example, acquire the necessary basic research skills to achieve theoretical progress in how to more efficiently convert solar energy into electric power. In contrast, a UAS graduate would learn how to apply the results of that research to the actual development of a photovoltaic system. Thus the UAS graduate can conduct applied research projects on how to apply this knowledge in the production of solar panels for rooftops.

In addition, the UAS mandate requires UASs to conduct applied research projects in cooperation with private-sector firms. Thus UASs frequently collaborate with (local) firms (Arvanitis et al., 2008), giving students opportunities to practice applied research on real-world problems during their studies. Consequently, given UAS goals, we expect UAS graduates to be well suited for integration into firms' R&D activities. We therefore focus on UAS campuses specializing in STEM, because we expect firms' technological R&D activities to concentrate in these fields.[4] As Schultheiss et al. (2019) show, UAS graduates are able to provide the missing link between R&D workers with academic knowledge and workers with vocational knowledge, thereby creating synergies that increase innovation outputs. Case studies of innovative Swiss firms, conducted by Backes-Gellner and Pfister (2019), also support the existence of such synergy effects. Therefore, we expect firms located near a UAS campus specializing in STEM to employ more R&D personnel to achieve efficiency gains. Likewise, we expect these firms to spend a larger percentage of their total wage sum on the wages of R&D employees, to further increase innovation outputs and improve competitiveness.

2.2. The introduction of UASs: A quasi-random process

The introduction of UASs in Switzerland in general and the location decisions in particular created a quasi-random outcome resulting from a very complex political process (Pfister

[4] A number of studies show the importance of STEM workers for adopting and generating innovation, and for increasing economic productivity and growth (e.g., Griliches, 1992; Jones, 1995; Peri et al., 2015; Winters, 2014). Moreover, firms with higher percentages of creative and STEM workers are more innovative (Brunow et al., 2018).

et al., 2018). To analyze the location and timing decisions, and to determine whether these decisions truly created a quasi-random outcome, Pfister et al. (2018) examined a large number of sources, including policy reports and legal documents from the federal, cantonal,[5] and municipal[6] governments; official bulletins and historical records; reports from the UAS commission and the UAS councils;[7] UAS annual reports; federal and cantonal laws and intercantonal agreements; and more than 100 articles in 16 newspapers from the relevant period. Given Switzerland's federalist political system, Pfister et al. (2018) find that both the temporal and spatial variations of UAS campus introductions are quasi-random.

Specifically, Pfister et al.'s (2018) analyses show that a political trench warfare within and between cantons primarily drove (a) the introduction of new campuses in a particular region and (b) the closing or relocation of old ones. Although the political authority conferring UAS accreditation was the federal government, the political units bearing the main financial burdens were the cantons. The federal government's legal requirements for UASs (see section 2.1)—a solid financial base, campuses large enough to accommodate a sizable number of students, and equally distributed campuses throughout Switzerland—led to a heated political debate between (and even within) cantons. Historical events, personalities, micropolitics, package deals, concessions, and coalition building (related to, e.g., the introduction of a new UAS campus specializing in a field of study other than STEM, such as business or health) became fundamental determinants of the quasi-random location decisions and time delays in the openings of UAS campuses. For example, the Bern campus opened in 1997 and closed again in 2003, due to federal merging and relocation requirements.

The process resulted in 15 STEM campuses belonging to five UASs in the German-speaking area of Switzerland. We focus on this area of the country (not the French- or Italian-speaking parts) because the VET system is most strongly embedded—both culturally and institutionally—in the German-speaking part (Bolli et al., 2018; Freitag and

5 Switzerland has 26 cantons, which function similarly to states in the U.S.

6 Municipalities (*Gemeinden*) are similar to U.S. counties.

7 See Online Appendix A for descriptions of the different institutional actors (including the UAS commission and the UAS councils) involved in the UAS introduction process.

Bühlmann, 2003). The overall variation in the location and the timing of the introduction of UAS STEM campuses was related to various political factors, not to a region's economic strength or level of innovation. As this variation was not foreseeable, it was thus unrelated to local economic characteristics.

Online Appendix A contains an in-depth description of the process leading to the introduction of UASs and generating the quasi-random variation, including an overview of UAS campus locations, introduction years, and illustrative examples. The qualitative evidence in Online Appendix A confirms the quasi-randomness of the introduction process. Results of a quantitative analysis of pre-treatment trends in Section 4.3 and extensive empirical evidence based on economic indicators from both ESS and other data in Online Appendix A strongly support the quasi-random distribution of UAS campuses. This appendix details the economic preconditions of UAS campus regions, the composition of the treatment and control groups, and any unobservable factors potentially determining UAS campus introductions. All these analyses support our argument that the introduction of UASs in Switzerland constitutes a quasi-random process.

3. Data

To estimate the effect of the supply shock of skilled labor on firms' employment of R&D personnel, we use the largest representative firm survey available in Switzerland, the ESS. The Swiss Federal Statistical Office (SFSO), which started the ESS in 1994, conducts it biennially, thus covering the relevant period of the UAS openings between 1997 and 2003. Every wave of the ESS comprises a new stratified random sample of all firms in Switzerland, with survey participation mandatory. Our data thus constitutes repeated cross-sections.

The ESS contains information on more than 300,000 firm-year observations between 1994 and 2014, and each firm provides detailed information on its employees and their tasks.[8] To determine the location of an employee's workplace, the ESS indicates the

[8] The number of employees that each firm reports in the survey depends on firm size: Firms with fewer than 20 employees report information on every employee; firms with 20 to 49 employees randomly report every second employee; and firms with 50 employees or more randomly report every third employee.

"mobilité spatiale" (MS) regions,[9] that is, homogeneous micro-regions whose boundaries rely on (among other things) regional mobility analyses and structural labor markets (Schuler et al., 2005). Therefore, MS regions are well suited for our analysis. The next higher administrative regions are the cantons; the next lower, the municipalities. Each canton consists of about four MS regions, and an MS region consists on average of about 22 municipalities.

Following Janssen et al. (2016), who exploit variation in workplace locations within firms at the cantonal level, we use the information on employees' workplace locations to determine the locations of firms' establishments.[10] We split firms by assigning all employees working in the same MS region to one establishment.[11]

Firms surveyed in the ESS also report the main job activity—e.g., construction, secretarial, R&D[12]—of their employees and the exact wage in October of the survey year, thereby allowing us to precisely measure firms' R&D personnel at the establishment level. From this information, we calculate two outcome variables that represent firms' R&D personnel (see appendix A for descriptive statistics).

First, the percentage of R&D personnel (RDP^{pct}) gives the fraction of employees with R&D as their main job activity relative to the total number of employees within an establishment (adjusted to full-time equivalents). We calculate this variable in the following way:

$$RDP_i^{pct} = \sum_{j=1}^{N_i} rd_j l_j \Bigg/ \sum_{j=1}^{N_i} l_j \tag{1}$$

with i as the establishment, j as the employee, N as the number of employee observations, rd as the binary indicator of R&D as main job activity, and l as the individual employment

However, as the data shows that some firms chose to report more observations than necessary, we do not rely on the three firm-size categories when calculating the variables for our estimations.

9 In 1982, a federal study defined the non-administrative MS regions (Schuler et al., 2005). Since then, the borders of these regions have not changed, except for minor revisions resulting from municipality mergers (Schuler et al., 2005).

10 The results in Table 2 are robust to restricting the sample to single-establishment firms (see online appendix B).

11 This procedure eliminates any biases that might result from fixing the location of a multi-establishment firm to, for example, the MS region where most of its employees work, even though the firm conducts R&D at an establishment in a different location.

12 R&D is one of 24 categories in the job activity variable.

level ($0 < l \leq 1$).[13] As Equation 1 shows, we adjust the variable to full-time equivalents by weighting each employee observation with the individual employment level, thereby avoiding potential biases caused by part-time employment.

Second, the percentage of R&D wages (RDW^{pct}) indicates the fraction of wages paid to R&D employees relative to the total wage sum. For this variable, we proceed similarly:[14]

$$RDW_i^{pct} = \sum_{j=1}^{N_i} w_j rd_j \Bigg/ \sum_{j=1}^{N_i} w_j \tag{2}$$

with w as the monthly wage.[15]

With this set of dependent variables, we can investigate whether firms employ more workers performing R&D, relative to other workers, and whether firms also spend more on total R&D personnel. As firms can report only one job activity per employee, our outcome variables can be considered lowered bounds; therefore, they are strong indicators for R&D-active personnel.

4. Methodology

4.1. Identification strategy

Using Pfister et al.'s (2018) identification strategy, we exploit the quasi-random variation in the location and the timing of UAS campus openings to estimate the causal effect of the resulting supply shock of skilled labor on firms' employment of R&D personnel. Between 1997 and 2003, 15 UAS STEM campuses opened in the German-speaking part of Switzerland (for an overview, see figure 1 and online appendix A), where the VET system is particularly strong. As we argue in Section 2.2, the openings of these campuses followed a quasi-random process.

[13] For individuals with $l > 1$ we set $l = 1$.

[14] Before aggregating at the establishment level, we deflate every wage observation in the dataset to 2010 prices according to the Consumer Price Index provided by the SFSO. See https://www.bfs.admin.ch/bfs/en/home/statistics/catalogues-databases.assetdetail.cc-d-05.02.08.html (last retrieved on September 6, 2018).

[15] Firms report wages in October of each survey year. To avoid any bias, we use the base salary, with no extra earnings such as overtime or bonus payments.

To estimate how firms adjust their R&D personnel after the educational supply shock, we apply the following DiD model:

$$\begin{aligned} Y_{i,t} = &\beta_0 + \beta_1 Treatment_{i,t-3} + \\ &\beta_2 TreatmentGroup_i + \beta_3 t + \beta_4 X_{i,t} + \mu_{i,t} \end{aligned} \tag{3}$$

In this model, Y is the dependent variable (RDP^{pct} or RDW^{pct}) for establishment i in survey year t. The treatment variable $Treatment$ equals one for establishments in the treatment group when the treatment sets in, that is, when the UAS campus has opened. The coefficient β_1 thus identifies the treatment effect we are interested in. Given the standard curriculum lenght of six semesters and the average graduation time of slightly more than three years,[16] we allow for a time lag of three years between the opening of a UAS campus and an expected treatment effect. The binary variable $TreatmentGroup$ identifies whether an establishment belongs to the treatment group or to the control group, that is, whether or not it is located within a region that is affected by a STEM UAS campus, thereby capturing time-invariant differences between establishments in the treatment and control groups. To control for time trends that are common to all establishments, we include a set of dummies indicating the survey year t. The vector X contains a set of establishment-level control variables and μ is the error term.[17]

As establishment-level control variables, we include the industry sector at the 2-digit level of the General Classification of Economic Activities (NOGA) 2002,[18] firm size in

[16] For example, the Winterthur campus opened in 1998. According to the standard curriculum of six semesters, the first graduates would have left the UAS and entered the labor market in 2001. As we use biennial data and thus do not observe firms in 2001, in Equation 3 we observe that $Treatment_{i,t-3} = 0$ if $t \leq 2000$ and $Treatment_{i,t-3} = 1$ if $t \geq 2002$ for all firms in the Winterthur campus treatment region. Likewise, for firms in the treatment region of the Burgdorf campus, which opened in 1997, $Treatment_{i,t-3} = 1$ if $t \geq 2000$. The three-year time lag, the most conservative lag for our model, might lead to an underestimation of the true treatment effect, because the lag does not cover students who stay at a UAS for more than six semesters (e.g., due to part-time work during studies).

[17] We cluster standard errors at the firm level, because establishments belonging to the same firm share common organizational structures affecting personnel decisions (among other things).

[18] In 1994, sampling was based on the "Allgemeine Systematik der Wirtschaftszweige" (ASWZ) 1985. We convert this classification to the NOGA 2002 according to the correspondence tables provided by the SFSO, see https://www.bfs.admin.ch/bfs/en/home/statistics/catalogues-databases/publications.assetdetail.176072.html (last retrieved on April 16, 2019) and https://www.bfs.admin.ch/bfs/en/home/statistics/catalogues-databases/publications.assetdetail.82758.html (last retrieved on April 16, 2019). Since 2010, sampling in the ESS is based on the NOGA 2008. However, the ESS also provides the NOGA 2002 industry sector for survey year 2010.

three categories as indicated in the Business and Enterprise Register (BUR),[19] and the canton[20] of a firm's main location.[21] We do so for two reasons. First, the ESS sampling procedure depends on these three characteristics and varies between survey years, affecting the composition of firms in our sample (e.g., general sample size increase since 2002, overrepresentation of single cantons within survey years). Second, independent of the treatment, the sampling characteristics influence our outcome variables and thus need controlling for (e.g., Lechner, 2010). Therefore, our analysis identifies the average treatment effect on the treated conditional on the three sampling characteristics of industry sector, firm size, and canton.

4.2. Definition of treatment and control groups

We use MS regions to define whether an establishment is treated or untreated based on its location. As Pfister et al. (2018) demonstrate, Swiss citizens commute only small travel distances, with around 90 percent commuting less than 25 kilometers (15.5 miles) to work. Moreover, Pfister's (2017) analysis and our additional analyses in Online Appendix A show that the net mobility of UAS graduates moving from the treatment to the control group and vice versa is extremely low. Following these arguments, we also assume that the local labor market for UAS graduates is restricted within a 25-kilometer travel-distance[22] radius of a UAS campus.

However, the ESS data contains regional information only at the MS region level, but

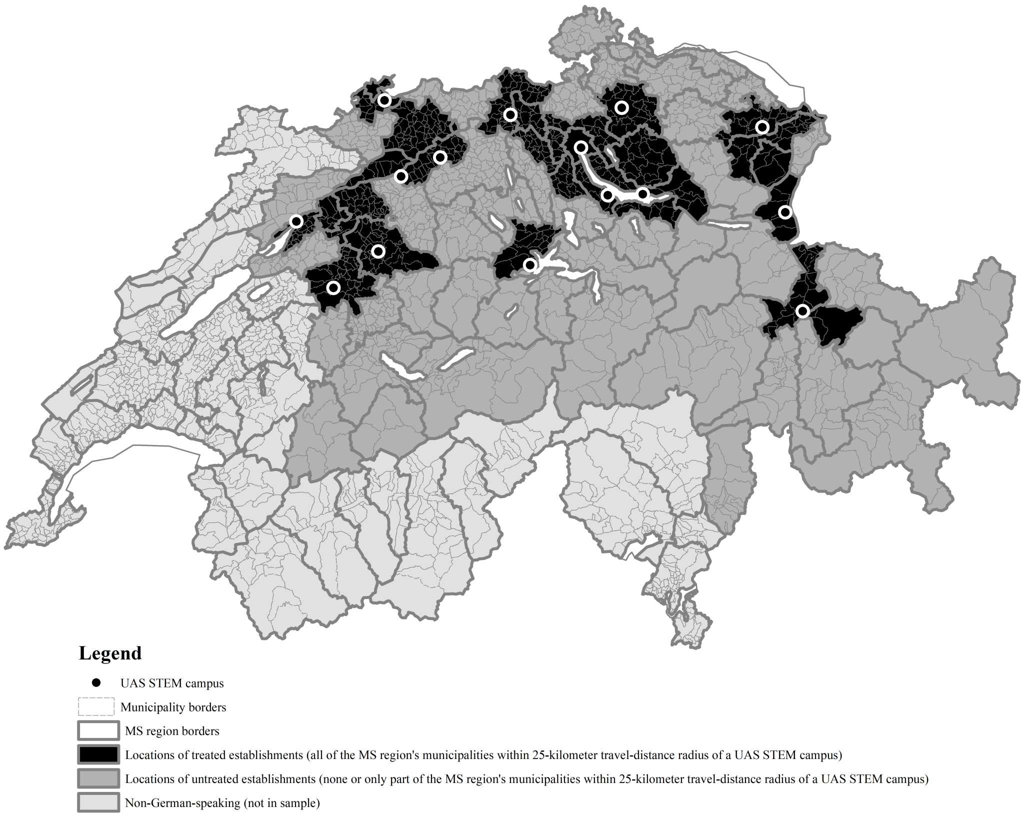
[19] The first category comprises firms with fewer than 20 employees; the second, firms with 20 to 49 employees; and the third, firms with 50 or more employees.

[20] Until 2000, sampling in the ESS was not based on firms' locations. Since 2002, it has been based on which of seven greater regions a firm is located in. However, cantons can request that the ESS draws samples representative for the respective cantons in single years. Therefore, cantons are the lowest regional level at which sampling actually takes place in the ESS.

[21] As the ESS does not provide information on a firm's main location, we reconstruct it in line with the SFSO (2016) definition of the main location as the location where the largest number of employees work. In other words, the main location is set to the canton with the most employee observations in the data. If the number of employee observations is equal for two or more cantons, the main location is set to the canton with the largest cumulative wage sum. If both the number of employee observations and the cumulative wage sum are equal for two or more cantons, the main location is set to the canton with the longest tenure of an individual employee. But if the main location cannot be identified according to this stepwise procedure, we drop the respective observations from our sample (20 establishment-year observations).

[22] We use Pfister et al.'s (2018) travel distance measure, calculated with the Google application programming interface.

Figure 1: Geographic locations of UAS campuses in STEM, treated establishments, and untreated establishments



Source: Authors' illustration with geodata from SFSO, GEOSTAT (Generalisierte Gemeindegrenzen der Schweiz, Ausgabe 2015) available from https://www.bfs.admin.ch/bfs/de/home/dienstleistungen/geostat/geodaten-bundesstatistik/administrative-grenzen/generalisierte-gemeindegrenzen.assetdetail.330759.html (last retrieved on April 16, 2019).

not at the municipality level as in Pfister et al.'s (2018) analysis. As the MS regions constitute a classification at a geographical level larger than municipalities (i.e., an MS region consists of several municipalities), we are not able to reconstruct the exact borders of the 25-kilometer area around a UAS campus with our data. Instead, we use Pfister et al.'s (2018) municipality-level data to identify how many of the municipalities belonging to an MS region are located within 25 kilometers of a UAS STEM campus. We calculate for each MS region the percentage of treated municipalities (i.e., the number of treated municipalities relative to the total number of municipalities within an MS region). To be conservative, we assign to the treatment group only establishments located in MS regions in which 100 percent of the MS region's municipalities are treated (i.e., within 25 kilometers of a UAS STEM campus). We then assign to the control group all establishments in MS regions in which less than 100 percent of the MS region's municipalities are treated. In other words, as soon as one municipality within an MS region is untreated, we assign the entire MS region to the control group. This assignment procedure leads to an underestimation of the true treatment effect, because the control group may also contain treated establishments within 25 kilometers of a UAS STEM campus. Our estimation results thus provide a lower bound of the true treatment effect.[23] Figure 1 graphically illustrates the geographic locations of UAS STEM campuses and those of treated and untreated establishments.

4.3. Assessment of parallel trends assumption

The crucial assumption of a DiD model is the parallel trends assumption—that both treatment and control groups have to show the same time trend in the dependent variable in absence of the treatment. In our case, the first UAS STEM campuses opened in 1997. With the three-year time lag, the first year in which we expect UAS graduates to enter local labor markets is three years later, in 2000.

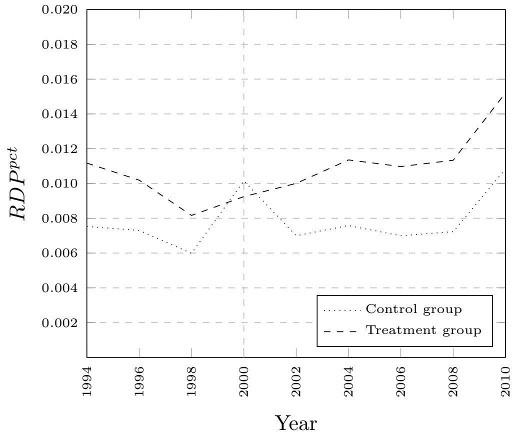
To investigate whether the parallel trends assumption holds in our sample, we plot the trends in the dependent variables for both the treatment and control groups. Before the treatment sets in, the two curves should follow the same time trend, that is, run parallel. First, we plot the raw means. Second, as we condition on the three sampling control variables—industry sector, firm size, and canton—in our DiD model (see section 4.1), we plot the predicted means from an OLS regression of the respective dependent variable on the three sampling control variables. For our DiD estimator to identify the causal effect of the introduction of UASs, parallel time trends in the predicted means suffice.

Figure 2 shows the time trends of the two dependent variables, percentage of R&D personnel (RDP^{pct}) and percentage of R&D wages (RDW^{pct}), throughout the observed period for the treatment and control groups. A look at the raw means in Figures 2a and 2c (i.e., without adjusting the values for differences that arise from changes in sampling between survey years) reveals a declining trend for both the treatment and control groups,

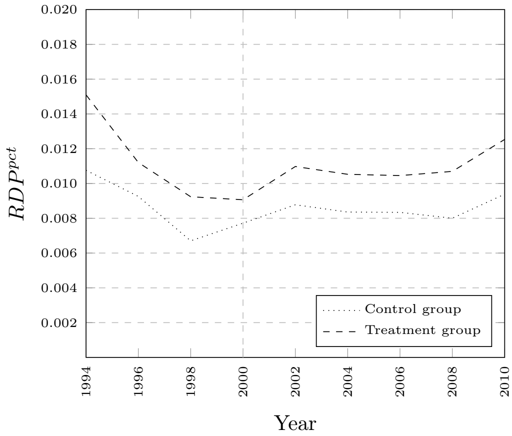
[23] The results in Table 2 are robust to increasing or decreasing the treatment radius between 20 and 40 kilometers (see online appendix B).

Figure 2: Trends of dependent variables in treatment and control groups

Panel (1): Percentage of R&D personnel (RDP^{pct})

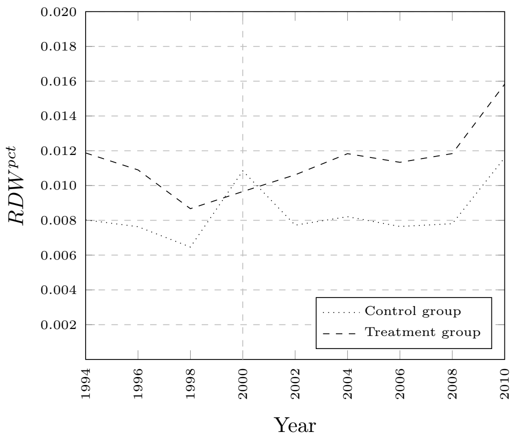


(a) Raw means

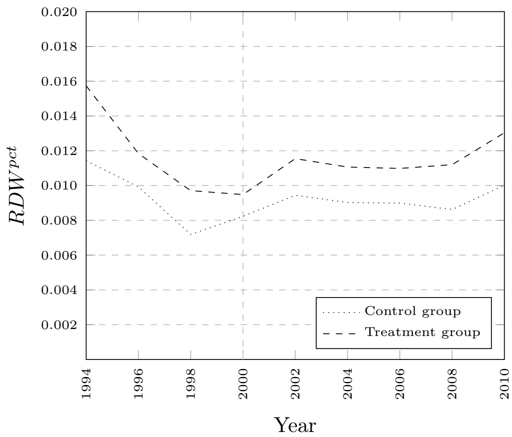


(b) Predicted means

Panel (2): Percentage of R&D wages (RDW^{pct})



(c) Raw means



(d) Predicted means

Source: Authors' illustrations based on data from the ESS.
Note: Predicted means stem from a linear regression of the respective dependent variable on the three sampling characteristics.

with the decline slightly stronger for the treatment group. Furthermore, the peak in the control group in 2000, the first treatment year in our model specification, appears odd at first glance. However, the predicted means in Figures 2b and 2d show that the pre-treatment trends run parallel and that the peak in the control group vanishes completely. Thus the sampling characteristics fully explain the slight differences in the trends of the treatment and control groups, implying that these differences are indeed unrelated to the treatment.

To further investigate whether the parallel trends assumption holds and whether the effect of the control variables is stable over time, we perform an OLS regression analysis for the pre-treatment period. We regress the dependent variables on the treatment group dummy, the three sampling control variables, and a set of survey year dummies, as well as their interactions with the treatment group dummy and the sampling control variables, as follows:

$$\begin{aligned} Y_{i,t} =& \gamma_0 + \gamma_1 TreatmentGroup_i + \gamma_2 t + \\ & \gamma_3 TreatmentGroup_i \times t + \gamma_4 X_{i,t} + \\ & \gamma_5 X_{i,t} \times t + \nu_{i,t} \end{aligned} \tag{4}$$

where ν is the error term.

Table 1 provides the results of these regressions. These results strengthen our interpretation of the graphs in Figure 2—that the pre-treatment time trends do not differ between the treatment and the control groups. None of the estimations show jointly significant interactions between treatment group and survey year dummies, even when we do not include the sampling control variables. Moreover, while the set of sampling control variables is jointly significant in all estimations, their interactions with the survey year dummies are not. Thus the effect of the control variables is stable over time. These results clearly show that assuming parallel pre-treatment trends for the two dependent variables, RDP^{pct} and RDW^{pct}, is reasonable.

In addition to assessing the parallel trends assumption, the empirical evidence on the quasi-randomness of UAS campus introductions in Online Appendix A further supports

Table 1: Pre-treatment trends tests

	RDP^{pct}			RDW^{pct}		
	(1)	(2)	(3)	(4)	(5)	(6)
$TreatmentGroup_i$	0.365**	-0.023	-0.504	0.385**	-0.018	-0.479
	(0.159)	(0.161)	(0.615)	(0.162)	(0.164)	(0.620)
Year (t): 1996	-0.023	0.072	-1.049	-0.039	0.055	-0.974
	(0.198)	(0.201)	(0.646)	(0.199)	(0.202)	(0.657)
Year (t): 1998	-0.154	0.166	-2.184**	-0.156	0.181	-2.209*
	(0.166)	(0.161)	(1.113)	(0.170)	(0.165)	(1.128)
$TreatmentGroup_i$	-0.076	0.143	1.145*	-0.058	0.166	1.087
$\times$1996	(0.214)	(0.193)	(0.685)	(0.217)	(0.195)	(0.696)
$TreatmentGroup_i$	-0.147	0.024	1.864	-0.164	0.010	1.901
$\times$1998	(0.207)	(0.197)	(1.189)	(0.212)	(0.201)	(1.207)
Controls	No	Yes***	Yes**	No	Yes***	Yes***
Controls $\times$ Year	No	No	Yes	No	No	Yes
F-test $TreatmentGroup_i \times t$	0.254	0.348	1.798	0.323	0.515	1.687
N	28,524	28,524	28,524	28,524	28,524	28,524
R^2	0.001	0.184	0.208	0.001	0.186	0.212

Source: Authors' calculations with data from the ESS.
Notes: Robust standard errors clustered at the firm level in parentheses. All models include intercept. Coefficients and standard errors are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

our identification strategy (see also section 2.2). More specifically, economic preconditions and other unobservable factors did not influence the spatial or temporal distribution of UAS campuses. Therefore, we argue that the DiD estimator identifies the causal effect of UAS campus introductions on R&D employment.

5. Results

5.1. Main results

Table 2 provides the OLS estimation results of the DiD approach specified in Equation 3, with coefficients representing percentage point changes. We find that treated establishments employ a significantly higher percentage of workers who perform R&D as their main job activity after the opening of a UAS STEM campus (columns 1 and 2). Given the sample mean of 1.02 percent, this treatment effect of 0.16 percentage points is also economically significant. The sampling control variables explain the time-invariant differences between the treatment and control groups, but do not substantially change the treatment effect.

Table 2: Main estimation results

	RDP^{pct}		RDW^{pct}	
	(1)	(2)	(3)	(4)
$Treatment_{i,t-3}$	0.166***	0.158***	0.143**	0.145**
	(0.060)	(0.055)	(0.061)	(0.056)
$TreatmentGroup_i$	0.227***	0.027	0.233***	0.035
	(0.055)	(0.054)	(0.056)	(0.056)
Year dummies	Yes***	Yes***	Yes***	Yes***
Controls	No	Yes***	No	Yes***
Sample mean of dep. var.	1.016	1.016	1.073	1.073
N	232,228	232,228	232,228	232,228
R^2	0.001	0.171	0.001	0.169

Source: Authors' calculations with data from the ESS.
Notes: Robust standard errors clustered at the firm level in parentheses. All models include intercept. Coefficients, standard errors, and sample mean of dep. var. are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Furthermore, we find that treated establishments spend a significantly larger percentage of their total wage sum on R&D personnel after the introduction of UASs (table 2, columns 3 and 4). Given the magnitude of 0.14 percentage points and the sample mean of 1.07, this wage effect is statistically significant at the five percent level, as well as economically significant. Again, conditioning on the sampling control variables leads to the treatment group dummy turning insignificant, while the treatment effect even slightly increases.

A look at the individual employee level reveals that the increase in the employment of R&D personnel does not coincide with a decrease in the average wage of an individual R&D employee. After the introduction of UASs, the average wage of an individual R&D worker employed at the establishments in our estimation sample increases steadily in both the treatment and control groups, with a larger increase in the treatment group (see appendix B). This descriptive evidence suggests that firms do not employ more R&D personnel in the form of UAS graduates as cheap replacements for academic university graduates, because in such a case the average wage of an individual R&D employee would have decreased.

Our estimation results indicate that firms' employing more R&D personnel is one channel through which tertiary education institutions influence innovation. Firms that experience an education-driven labor supply shock after the openings of UAS STEM campuses yield a significantly higher R&D intensity as measured by the percentage of R&D personnel and the percentage of wages paid to R&D personnel.

5.2. Robustness checks

To test the robustness of our DiD estimation results, we estimate a large number of alternative specifications of our model. In this section, we briefly summarize these robustness checks. We provide the detailed analyses, including the corresponding regression tables, in the Online Appendix.

We perform two analyses that account for unobserved characteristics, thereby helping us detect any violations of the parallel trends assumption that our assessments in Section 4.3 did not. First, in our empirical assessment of the quasi-randomness of UAS campus introductions in Online Appendix A, we consider unobservable campus region-specific characteristics (e.g., level and growth of the economy) by including campus region-specific fixed effects (FE) and trends in our estimations. In addition to determining UAS campus locations, such characteristics could affect the outcome of the treatment. We find that the treatment effects of our main specification persist even when we include unobservable campus region-specific characteristics. This finding represents strong evidence for the quasi-randomness of UAS campus introductions and for the treatment effect's independence from campus region-specific characteristics.

Second, to account for unobserved time-invariant establishment characteristics, we perform an FE estimation in Online Appendix B. As we cannot track firms over time in the ESS data due to its repeated cross-sections, we group the establishment-level observations according to observable characteristics (MS region, industry sector, and firm size) to obtain an unbalanced quasi-panel. Using these establishment groups as our unit of observation, we perform a quasi-panel FE estimation. The results of this estimation confirm the treatment effects of our DiD analysis in significance and size, indicating that unobserved time-invariant establishment characteristics do not explain the treatment effect.

Moreover, Online Appendix B shows that our main results are robust to a variety of alternative specifications of the model parameters and the sample composition. We demonstrate that econometrically reasonable decreases or increases of the treatment radius do not alter the main result. To ensure a correct assignment of employees to establishments and thus to test the robustness of our assignment procedure for multi-establishment firms (see section 3), we restrict the sample to single-establishment firms and find similar effects. We also show that our results are robust to excluding very large firms (5,000 or more employees) from the sample and to clustering standard errors at the regional (instead of at the firm) level.

In sum, all robustness checks confirm the correct specification of our DiD model. Neither unobservable characteristics nor the model parameters explain our findings. Therefore, we argue that our main results in Section 5.1 indicate the causal treatment effect of UAS introductions on R&D employment. While these results show that firms experiencing a supply shock of skilled labor engage more intensively in R&D, we do not yet know precisely which types of firms drive the effects. Therefore, in Section 5.3 we further assess the mechanisms underlying this finding.

5.3. Effect heterogeneity

After analyzing the average effect of the introduction of UASs on firms' R&D personnel, we investigate whether this effect is heterogeneous. The finding that, on average, establishments treated by a UAS STEM campus (a) have a larger percentage of employees with R&D as their main job activity and (b) spend a larger percentage of their total wage sum on R&D employees either could result from firms just starting to engage in R&D (potential start-ups) or from firms engaging more intensively in R&D while having conducted R&D before the introduction of a UAS. Moreover, certain types of firms (e.g., small firms or firms in specific industry sectors) might profit more than other types from the UAS graduates' skills in R&D.

To identify which firms drive our findings, we examine whether the effect of the introduction of UASs is heterogeneous across different types of firms. We do so in three steps. First, by estimating Equation 3 with an alternative outcome variable, we investigate whether establishments just starting to engage in R&D determine our findings. Second, we assess whether the effect varies with the size of the firm to which an establishment belongs. Third, we investigate whether the effect differs with regard to a firm's industry sector.

To shed light on the question of whether establishments that start to engage in R&D only after the supply shock of skilled labor contribute to the effects we find, we construct a binary dependent variable RD^{bin} that indicates whether a firm conducts R&D or not. The variable RD^{bin} equals one if a firm has at least one R&D employee (i.e., if $RDP^{pct} > 0$). Then we estimate Equation 3 with RD^{bin} as the dependent variable.

Table 3 shows the result of this estimation. We find that, after the introduction of UASs, treated establishments have a substantially higher probability of conducting R&D than before. Thus firms recently starting to engage in R&D at least partly explain the treatment effects we find. Unfortunately, as our data comprises repeated cross-sections, we cannot track firms over time and thus cannot definitively determine whether those firms recently starting to engage in R&D are pre-existing firms or start-ups. However, by using employees' tenure as proxies for firm and establishment age to separate existing firms and start-ups, we conduct further analyses and present detailed results in Online Appendix B.

While the construction of these proxies calls for some caution in interpreting the results across age classes, the analyses still strongly indicate that not only pre-existing firms start engaging in R&D but also start-ups and younger firms (i.e., whose employees have only a very short maximum tenure as proxy for firm and establishment age).

Table 3: Estimation results on the probability to conduct R&D

	RD^{bin}	
	(1)	(2)
$Treatment_{i,t-3}$	0.037	0.580***
	(0.168)	(0.158)
$TreatmentGroup_i$	0.549***	0.178
	(0.157)	(0.152)
Year dummies	Yes***	Yes***
Controls	No	Yes***
Sample mean of dep. var.	4.608	4.608
N	232,228	232,228
R^2	0.001	0.157

Source: Authors' calculations with data from the ESS.
Notes: Robust standard errors clustered at the firm level in parentheses. All models include intercept. Coefficients, standard errors, and sample mean of dep. var. are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

While firms that start to engage in R&D contribute to the main effects we find, these effects might still be heterogeneous across firm-size classes. Therefore, to assess effect heterogeneity, we split our sample into subsamples of establishments belonging to firms with different firm sizes. To determine a firm's size, we use the self-reported information on the total number of employees[24] (i.e., the total number in all of a firm's establishments taken together) available in the ESS and group firms according to the size classes proposed by the

[24] The self-reported firm size contains the total number of employees at the time of the survey. In comparison, the firm-size category we use as a control variable (see section 4.1) is a stratification criterion in the ESS and contains information from the BUR. In the effect heterogeneity analyses, we still control for the firm-size category from the BUR.

OECD (2015, p. 206). We then estimate Equation 3 (at the establishment level) separately for each subsample, with RDP^{pct}, RDW^{pct}, and RD^{bin} as the dependent variables.

Table 4 provides the estimated treatment effects for the different firm-size classes. These results suggest that establishments belonging to very small firms (from 5–9 employees) and those belonging to very large firms (5,000 or more employees) profit most from the introduction of UASs. For very small firms, the increase in R&D-specific labor supply might have facilitated the recruitment of R&D personnel. Moreover, for UAS graduates, a job position at a very small firm might be a suitable start for a career in R&D. Slightly larger firms (10–20 employees) intensify their engagement in R&D due to the improved recruitment options in the form of UAS graduates. The marginally significant negative effect on the percentage of R&D wages indicates that medium-sized firms (250–499 employees) might replace their previous R&D personnel with UAS graduates, because these firms might have a competitive advantage in the local labor markets but otherwise do not change their engagement in R&D. In contrast, larger firms (1,000–4,999 employees) appear to establish R&D in regions where they were not previously active. Very large firms[25] (5,000 or more employees) also open new R&D establishments and intensify their engagement in R&D as well.

These results are robust to alternative specifications of firm-size classes with more equal class sizes. Online Appendix B shows the results for dividing firms into quintiles and deciles of the firm-size distribution. While these specifications do not allow the assessment of very large firms, the results are structurally very similar, with small firms experiencing the strongest effects.

Another source for heterogeneous effects might be that, as one would expect, only firms in industry sectors related to STEM profit from the openings of UAS STEM campuses. To examine effect heterogeneity across industry sectors, we perform subsample estimations for establishments belonging to firms in different industry sectors. We use the main categories of the NOGA 2002 (see also section 4.1) as the industry sectors. Then, as we did for the subsamples of different firm-size classes, we estimate Equation 3 (at the establishment level)

[25] The 3,027 establishments in the subsample of firms with 5,000 or more employees belong to 128 firms. The main results in Table 2 are robust to excluding these establishments (see online appendix B).

Table 4: Estimation results by firm size class

	Firm size (S_i)	N	RDP^{pct} (1)	RDW^{pct} (2)	RD^{bin} (3)
$Treatment_{i,t-3}$	$S_i \leq 4$	53,029	0.076	0.064	0.181
			(0.122)	(0.124)	(0.170)
	$5 \leq S_i \leq 9$	35,134	0.336**	0.345**	0.615**
			(0.138)	(0.142)	(0.292)
	$10 \leq S_i \leq 19$	29,300	0.355*	0.300	0.592
			(0.183)	(0.188)	(0.450)
	$20 \leq S_i \leq 49$	36,799	0.253	0.226	0.548
			(0.156)	(0.160)	(0.460)
	$50 \leq S_i \leq 99$	22,644	0.287*	0.259	0.515
			(0.165)	(0.172)	(0.602)
	$100 \leq S_i \leq 249$	22,190	-0.125	-0.136	-0.216
			(0.173)	(0.176)	(0.586)
	$250 \leq S_i \leq 499$	12,062	-0.319	-0.356*	-0.910
			(0.202)	(0.213)	(0.743)
	$500 \leq S_i \leq 999$	8,348	-0.100	-0.108	-0.147
			(0.235)	(0.235)	(0.894)
	$1,000 \leq S_i \leq 4,999$	9,695	0.159	0.142	1.120*
			(0.193)	(0.197)	(0.677)
	$5,000 \leq S_i$	3,027	0.523***	0.490**	3.928***
			(0.194)	(0.189)	(1.302)

Source: Authors' calculations with data from the ESS.
Notes: Results from separate regressions. Robust standard errors clustered at the firm level in parentheses. All models include intercept, treatment group dummy, year dummies, and sampling control variables. Coefficients and standard errors are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Estimation results by industry sector

		Industry sector ($NOGA2002_i$)	N	RDP^{pct} (1)	RDW^{pct} (2)	RD^{bin} (3)
$Treatment_{i,t-3}$	A	Agriculture and forestry	5,106	-0.164	-0.172	-0.063
				(0.150)	(0.158)	(0.213)
	C	Mining and quarrying	824	0.070	-0.098	0.995
				(0.370)	(0.383)	(2.590)
	D	Manufacture of goods	53,852	0.366**	0.352**	1.519***
				(0.156)	(0.163)	(0.532)
	E	Electricity, gas, and water supply	1,240	0.440	0.439	-0.759
				(0.270)	(0.267)	(1.878)
	F	Construction	12,965	0.007	0.005	-0.345
				(0.021)	(0.025)	(0.272)
	G	Wholesale and retail trade	45,028	-0.001	0.002	0.085
				(0.045)	(0.045)	(0.199)
	H	Hotels and restaurants	9,626	0.004	0.005	0.113*
				(0.003)	(0.003)	(0.064)
	I	Transport, storage, and communication	13,879	-0.058	-0.062	-0.546
				(0.043)	(0.047)	(0.451)
	J	Financial interme- diation; insurance	16,158	0.035	0.031	0.286
				(0.064)	(0.062)	(0.267)
	K	Real estate, renting; other business activities	36,779	0.174	0.120	0.238
				(0.241)	(0.244)	(0.445)
	M	Education	6,164	-0.127	-0.178	-0.149
				(0.192)	(0.206)	(0.669)
	N	Health, veterinary, and social work	13,295	-0.167	-0.174	-0.599
				(0.126)	(0.130)	(0.439)
	O	Other community, social, and personal service activities	17,312	0.540**	0.540**	1.171***
				(0.214)	(0.215)	(0.404)

Source: Authors' calculations with data from the ESS.
Notes: Results from separate regressions. Robust standard errors clustered at the firm level in parentheses. All models include intercept, treatment group dummy, year dummies, and sampling control variables. Coefficients and standard errors are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Nomenclature of NOGA 2002 categories provided by SFSO (2002), titles shortened for illustration (original titles provided in appendix C).

for each industry-sector subsample, with RDP^{pct}, RDW^{pct}, and RD^{bin} as the dependent variables.

Our assessments of effect heterogeneity across industry sectors, shown in Table 5, indicate that establishments belonging to firms in the "manufacture of goods" and "other community, social, and personal service activities" sectors drive our main results. Establishments belonging to firms in the "manufacture of goods" sector started to engage in R&D and intensified their engagement in R&D after the introduction of UASs. We find similar effects for the "other community, social, and personal service activities" sector, which comprises, among other things, television and entertainment companies. As expected, establishments belonging to firms in sectors unrelated to STEM remain unaffected when treated by a UAS STEM campus or its graduates.[26] One exception is establishments in the "hotels and restaurants" sector, which has a slightly higher probability of conducting R&D, possibly because the availability of UAS graduates enabled these establishments to perform R&D in the first place.

In sum, our assessments of effect heterogeneity suggest that establishments belonging to firms with five to nine employees and those belonging to firms with 5,000 employees or more, as well as establishments belonging to firms in the "manufacture of goods" and "other community, social, and personal service activities" sectors drive our main results. Furthermore, firms' starting to engage in R&D contributes to these results. However, as the SFSO changed the sampling procedure for the ESS with the 2002 survey, and as firms in some of the subsamples might be underrepresented before 2002, our assessments of effect heterogeneity should be interpreted with some caution. Nonetheless, they contribute to a better understanding of where the overall treatment effect might originate.

5.4. Variation of treatment effects over time

To analyze whether the treatment effect remains stable over time, we estimate an alternative specification of our DiD model considering the years since treatment (y). In so doing,

[26] When examining UAS STEM campuses, we do not expect any treatment effects for industry sectors not involved in STEM activities. For an analysis of the effect of UASs on establishments in sectors such as "education" or "health, veterinary, and social work," campuses in other fields would have to be considered. Our main results in Table 2 are robust to excluding these establishments.

we follow Autor's (2003) standard procedure and now include y as an indicator for the temporal distance of an observation to the treatment year (instead of including a binary treatment variable), with the control group observations serving as the reference. As the ESS has a biennial structure, we set y to the next lower value if y is an uneven number. For example, for firms affected by the opening of the Rapperswil campus in 2001, $y = 0$ for firms observed in 2002, $y = 2$ for firms observed in 2004, etc.

Figure 3 shows the treatment effects over time. Figures 3a and 3c plot the raw means and the corresponding 95-percent confidence intervals of the dependent variables percentage of R&D personnel and percentage of R&D wages, respectively. In the pre-treatment period, the number of observations in the data is considerably lower, leading to larger confidence intervals. Although, as in Figure 2, the variable means suggest a declining pre-treatment trend, the confidence intervals include the control group mean (with the exception of $y = -4$), indicating that this declining trend is not statistically significant. The post-treatment period shows a clear upward trend in the dependent variables, indicating an increase of the treatment effect over time.

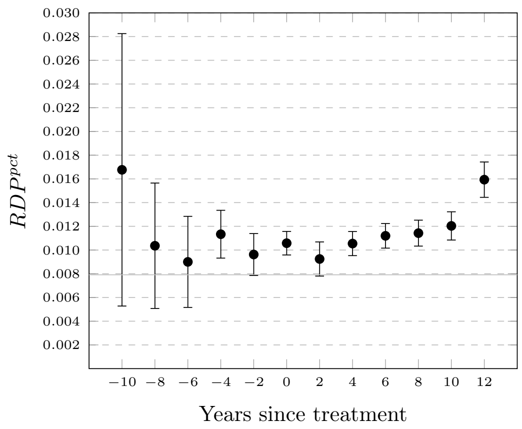
Figures 3b and 3d show that none of the pre-treatment coefficients is statistically different from zero, whereas after at least four years, all coefficients are positive and statistically significant at the one percent level. The panels plot the coefficients and their 95-percent confidence intervals from OLS regressions of the respective dependent variable on years since treatment, survey year dummies, and sampling control variables (appendix D includes the detailed regression results). The results of these regressions also confirm our analyses in Section 4.3, suggesting parallel pre-treatment trends conditional on the sampling control variables. Furthermore, the treatment effect persists over time.

6. Conclusion

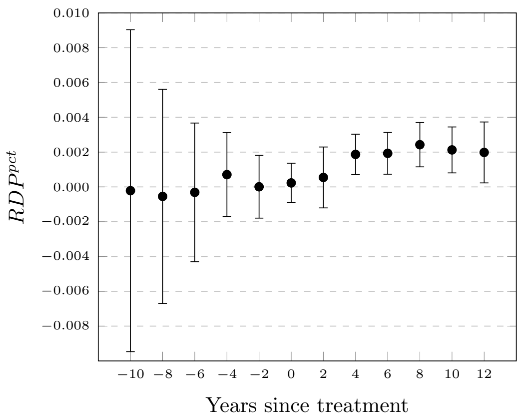
In this paper, we investigate how an exogenous increase in skilled labor supply resulting from the introduction of UASs in Switzerland influences the employment of R&D personnel in treated firms, in terms of both employment and wages paid to R&D personnel. Firms located near a UAS STEM campus experience a supply shock of skilled labor in the form

Figure 3: Variation of treatment effects over time

Panel (1): Percentage of R&D personnel (RDP^{pct})

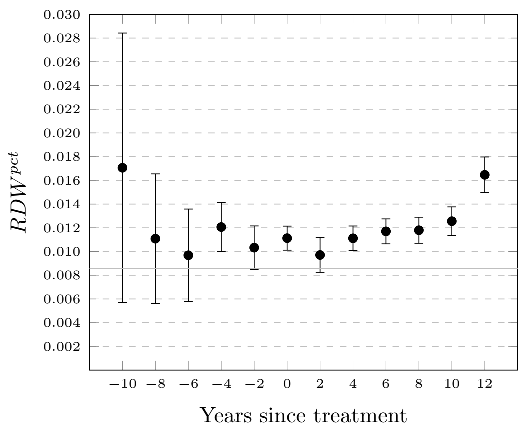


(a) Raw means

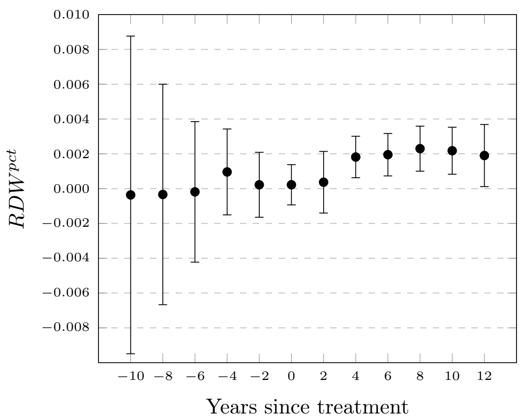


(b) Estimation coefficients

Panel (2): Percentage of R&D wages (RDW^{pct})



(c) Raw means



(d) Estimation coefficients

Source: Authors' illustrations based on data from the ESS.
Notes: Estimation coefficients stem from the regressions in Table D1. In addition to raw means or estimation coefficients, graphs show the respective 95-percent confidence intervals. The solid horizontal lines in panels (a) and (c) show the raw mean for the control group as the reference.

of UAS STEM graduates entering the regional labor markets.

Applying a DiD design that exploits the quasi-random variation in the location and the timing of UAS campus openings, we find that the percentage of R&D personnel relative to total personnel (i.e., the percentage of employees with R&D as their main job activity) in treated establishments increases significantly in comparison to untreated establishments. Moreover, we find that treated establishments spend a higher percentage of their total wage sum for R&D personnel, measured as the percentage of R&D wages (the sum of wages paid to R&D personnel relative to the total wage sum).

We conduct further analyses to examine which types of firms are responsible for the effects we find. First, these analyses suggest that firms' just starting to engage in R&D is one determinant of these effects. Second, both very small firms (particularly those with five to nine employees and thus possibly start-ups) and very large firms (with 5,000 or more employees) profit from the introduction of UASs. Third, firms in the "manufacture of goods" and "other community, social, and personal service activities" sectors conduct more R&D, thereby positively contributing to the overall effects.

Our findings suggest that the policy reform of introducing UASs in the German-speaking part of Switzerland provided firms with R&D personnel, thereby laying the foundation for increasing innovation activities of treated firms. The easier availability of labor with R&D skills to firms in the treated regions and the resulting incentives for a stronger engagement of those firms in R&D foster the employment of—and increase the budget spent on—R&D personnel, thereby providing one potential channel for an increase in innovation activities in the treated regions. Therefore, firms' using the R&D-specific skill resources of UAS graduates for their R&D purposes constitutes one of the underlying mechanisms leading to the increase in patenting activities that Pfister et al. (2018) found.

Our results provide important insights for policymakers designing reforms aimed at increasing firms' innovation activities through a tertiary education expansion (along the lines of UASs in Switzerland). The the particular combination of sound professional knowledge and applied research skills that STEM UASs provide is an effective means of stimulating R&D even in firms that may not have yet conducted it. With UAS graduates possessing skills tailored specifically for the R&D requirements of both small firms and firms starting to engage in R&D for the first time, a tertiary education expansion leading to the availability of such skills in regional labor markets both promotes and increases firms' innovation activities.

Appendices

Appendix A. Descriptive statistics for dependent variables

Table A1: Descriptive statistics for percentage of R&D personnel (RDP^{pct})

	Control group			Treatment group		
Year	N	Mean	SD	N	Mean	SD
1994	3,633	0.753	6.597	6,736	1.117	8.083
1996	2,992	0.730	6.371	5,694	1.019	7.666
1998	3,433	0.599	5.068	6,036	0.816	6.429
2000	3,362	1.015	7.629	6,062	0.925	7.334
2002	14,155	0.700	5.489	22,710	1.001	7.286
2004	14,300	0.758	6.114	24,471	1.136	8.066
2006	14,415	0.699	5.690	24,790	1.097	7.775
2008	14,606	0.723	5.921	24,505	1.134	7.961
2010	14,815	1.084	7.643	25,513	1.521	9.472
Total	85,711	0.791	6.271	146,517	1.148	8.049

Source: Authors' calculations with data from the ESS.
Note: Variable values multiplied by 100 to represent percentages.

Table A2: Descriptive statistics for percentage of R&D wages (RDW^{pct})

	Control group			Treatment group		
Year	N	Mean	SD	N	Mean	SD
1994	3,633	0.802	6.663	6,736	1.187	8.303
1996	2,992	0.763	6.396	5,694	1.090	7.898
1998	3,433	0.646	5.302	6,036	0.867	6.617
2000	3,362	1.084	7.842	6,062	0.966	7.431
2002	14,155	0.772	5.805	22,710	1.062	7.472
2004	14,300	0.821	6.330	24,471	1.183	8.159
2006	14,415	0.765	5.944	24,790	1.134	7.826
2008	14,606	0.781	6.147	24,505	1.184	8.059
2010	14,815	1.160	7.886	25,513	1.583	9.602
Total	85,711	0.856	6.500	146,517	1.200	8.171

Source: Authors' calculations with data from the ESS.
Note: Variable values multiplied by 100 to represent percentages.

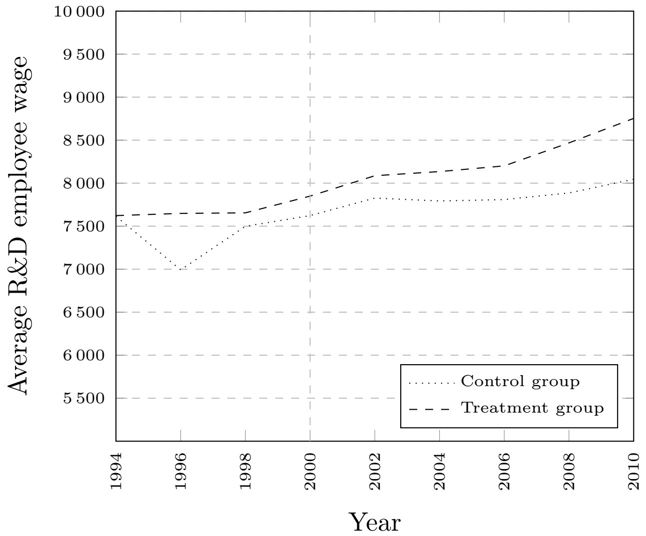
Table A3: Descriptive statistics for probability to conduct R&D (RD^{bin})

	Control group			Treatment group		
Year	N	Mean	SD	N	Mean	SD
1994	3,633	3.799	19.119	6,736	4.765	21.305
1996	2,992	3.643	18.739	5,694	4.724	21.218
1998	3,433	3.292	17.844	6,036	4.092	19.812
2000	3,362	4.610	20.974	6,062	4.223	20.113
2002	14,155	4.076	19.775	22,710	4.716	21.199
2004	14,300	4.231	20.130	24,471	4.704	21.172
2006	14,415	4.176	20.005	24,790	4.627	21.007
2008	14,606	4.005	19.609	24,505	4.705	21.175
2010	14,815	5.089	21.979	25,513	5.679	23.145
Total	85,711	4.244	20.160	146,517	4.821	21.422

Source: Authors' calculations with data from the ESS.
Note: Variable values multiplied by 100 to represent percentages.

Appendix B. R&D employee wage at the individual level

Figure B1: Development of average R&D employee wage at the individual level (in Swiss Francs)



Source: Authors' illustrations based on data from the ESS. Calculations at the individual employee level.

Appendix C. NOGA 2002 categories of industry sector

Table C1: NOGA 2002 categories of industry sector

Category	Title
A	Agriculture and forestry
B	Fishing and fish farming
C	Mining and quarrying
D	Manufacture of goods
E	Electricity, gas, and water supply
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and consumer durables
H	Hotels and restaurants
I	Transport, storage, and communication
J	Financial intermediation; insurance (excluding compulsory social security)
K	Real estate, renting, and related activities; other business activities
L	Public administration and defence; compulsory social security
M	Education
N	Health, veterinary, and social work
O	Other community, social, and personal service activities
P	Private household
Q	Extra-territorial organizations and bodies

Source: SFSO (2002)
Notes: Categories B, P, and Q not included in the ESS sample we use for our estimations. Category L excluded because it does not contain private firms.

Appendix D. Variation of treatment effects over time

Table D1: Estimation results over time

		RDP^{pct}		RDW^{pct}	
		(1)	(2)	(3)	(4)
Years since treatment	-10	0.953	-0.022	0.934	-0.036
		(0.595)	(0.472)	(0.589)	(0.466)
	-8	0.302	-0.055	0.327	-0.034
		(0.322)	(0.314)	(0.330)	(0.323)
	-6	0.202	-0.031	0.222	-0.019
		(0.216)	(0.203)	(0.219)	(0.206)
	-4	0.414***	0.071	0.438***	0.096
		(0.135)	(0.123)	(0.138)	(0.126)
	-2	0.233**	0.001	0.253**	0.022
		(0.100)	(0.092)	(0.104)	(0.095)
	0	0.295***	0.023	0.287***	0.022
		(0.058)	(0.058)	(0.060)	(0.059)
	2	0.134	0.054	0.117	0.037
		(0.094)	(0.089)	(0.095)	(0.090)
	4	0.345***	0.187***	0.333***	0.182***
		(0.064)	(0.059)	(0.066)	(0.061)
	6	0.337***	0.193***	0.327***	0.195***
		(0.063)	(0.061)	(0.064)	(0.062)
	8	0.379***	0.243***	0.354***	0.230***
		(0.067)	(0.065)	(0.068)	(0.066)
	10	0.419***	0.213***	0.408***	0.218***
		(0.072)	(0.067)	(0.073)	(0.069)
	12	0.528***	0.198**	0.499***	0.190**
		(0.094)	(0.089)	(0.096)	(0.091)
Year dummies		Yes***	Yes***	Yes***	Yes***
Controls		No	Yes***	No	Yes***
Sample mean of dep. var.		1.016	1.016	1.073	1.073
N		232,228	232,228	232,228	232,228
R^2		0.001	0.171	0.001	0.169

Source: Authors' calculations with data from the ESS.
Notes: Robust standard errors clustered at the firm level in parentheses. All models include intercept. Coefficients, standard errors, and sample mean of dep. var. are multiplied by 100 to represent percentage point changes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Online Appendix

The Online Appendix is available on the Elsevier website.

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