The Journal of Technology Transfer (2022) 47:63–118
https://doi.org/10.1007/s10961-020-09839-w

Innovation effects of universities of applied sciences: an assessment of regional heterogeneity

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Accepted: 15 December 2020 / Published online: 5 February 2021

Abstract
The literature on the economics of science and technology shows that academic universities—institutions focusing on basic research—positively affect innovation activities in regional economies. Less is known about the innovation effects of universities of applied sciences (UASs)—bachelor-granting three-year colleges teaching and conducting applied research. Furthermore, the evidence for positive innovation effects is predominantly based on average effects, while heterogeneity in innovation effects due to the economic environment is far less considered. By exploiting a public policy development in Switzerland that led to the quasi-random establishment of UASs, we investigate the regional heterogeneity in innovation effects of these UASs. We rely on patent and business census data and analyze the influence and importance of three economic preconditions—labor market size, labor market density and high tech intensity—on innovation effects of UASs. Our results show that only regions with a large or a dense enough labor market or with an above average high tech intensity experience significant innovation effects of UASs. Comparing the relative importance of the three economic preconditions, we find that labor market size is the most important factor that drives heterogeneity in innovation effects of UASs.

Keywords Higher education research institutions · Innovation · Public R&D · Regional heterogeneity

JEL Classification I23 · O31 · O32 · R11

1 Introduction

The question of whether higher education institutions affect innovation has been widely discussed in both the theoretical (e.g Aghion and Howitt 2009; Bercovitz and Feldman 2006) and empirical (e.g. Barra and Zotti 2018; Jaffe 1986; Link and Rees 1990; Lööf and Broström 2008) literature on the economics of science and technology (Audretsch

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et al. 2002). A number of recent papers—using the establishment of universities to identify innovation effects—show, on average, an increase in patenting activities in the respective regions by between 7% and 32% (Andrews 2019; Cowan and Zinovyeva 2013; Toivanen and Väänänen 2016). These studies mostly concentrate first on academic universities and second on the average innovation effects across regions. Thereby, both the innovation effects of other types of higher education institutions and the heterogeneity of these innovation effects linked to regional characteristics are neglected.

However, regarding different types of higher education institutions, the literature on the economics of science and technology shows that higher education institutions focusing on applied research—as compared to basic research—are especially likely to cooperate with the local industry and, therefore, have a higher propensity to contribute to positive innovation effects (Toner 2010). Thus, the current, predominant emphasis on the analysis of innovation effects of universities, i.e. of basic research, risks to underestimate potential innovation effects of higher education institutions in general.

Regarding regional heterogeneity in innovation effects of higher education institutions, the corresponding literature points to the importance of examining the heterogeneity linked to regional differences in economic preconditions (Ghinamo 2012). The theoretical argument behind these reasoning is that agglomeration economies—externalities generated by the grouping of individuals or firms in cities or industrial clusters (Glaeser 2010)—strengthen innovation effects. Indeed, economic preconditions such as a large or a dense labor market or high tech intensive industries positively intensify the innovation effects of universities (Agrawal and Cockburn 2003; Akhvlediani and Cieślik 2017; Feldman 1994; Kantor and Whalley 2014; Varga 2000). However, it remains unclear to what extent the economic preconditions associated with agglomeration effects cause heterogeneous innovation effects of higher education institutions that teach and conduct applied research. Yet, against the background of a high propensity of such institutions to cooperate with the local industry (Toner 2010), agglomeration economies might affect innovation effects very differently than in the case of universities. However, this question has not been studied so far.

We close this research gap by studying the heterogeneous innovation effects of the establishment of universities of applied sciences (UASs)—bachelor-granting three-year colleges teaching and conducting applied research—in Switzerland, a country repeatedly ranked as one of the most innovative countries in the world (WIPO et al. 2019). The establishment of UASs is useful for analyzing heterogeneity in innovation effects linked to economic preconditions for two reasons. First, the location of the newly established UASs in Switzerland was chosen in a quasi-random manner, i.e., it can be treated as an exogenous education expansion (Pfister et al. 2021; Pfister 2017), and thus helps to identify causal effects.

Second, UASs are shown to interact with the regional economy in different ways. They cooperate with local firms (Arvanitis et al. 2008)—having also an effect on firms farther away from the research frontier and from doing research on their own—, increase the share of R&D personnel in local firms (Lehnert et al. 2020), and positively affect innovation in general (Pfister et al. 2021). In addition, UAS graduates followed a vocational education and training track before studying at a UAS and, thereby, combine practical vocational skills with applied research knowledge. This skill combination is of particular importance for the innovative activities of small and medium sized firms (Backes-Gellner and Pfister 2019) that are characteristic of Swiss regional economies. This evidence of linkages between UASs and the regional economy reveals that differences in regional economic preconditions can lead to differences in regional innovation effects of UAS, potentially through agglomeration economies.

To assess agglomeration economies, we look at three economic preconditions that have previously been shown to lead to heterogeneity in regional innovation patterns (e.g. Carlino et al. 2007; Bellucci and Pennacchio 2016; Feldman 1994; Jaffe et al. 1993; Orlando and Verba 2005): (1) *labor market size*, i.e., a region's total employment, (2) *labor market density*, i.e., a region's employment relative to its territory and (3) *high tech intensity*, i.e., a region's employment in high tech industries. We expect the innovation effects from the newly established UASs to increase with increases in these three economic preconditions. Furthermore, we contribute to the literature on the economics of science and technology by analyzing which of these economic preconditions play the most important role in fostering innovation effects.

In our empirical analysis, we match three different data sets using municipalities—the smallest political entities in Switzerland—to spatially merge data on (1) the UAS establishment, (2) economic preconditions and (3) innovation. First, to identify regions with a newly established UAS, we build on a dataset by Pfister et al. (2021). We assign municipalities to either a treatment group (i.e., within a 25 kilometer radius around a newly established UAS) or the control group (i.e., outside a 25 kilometer radius around a newly established UAS). Thereby, we focus on campuses for engineering, IT and the life sciences, i.e., campuses with STEM fields, because, only their output can be measured reasonably well with patents—compared with campuses, e.g, for art and design or for social work. Second, to account for economic preconditions and approximate our three agglomeration measures, i.e., *labor market size*, *labor market density*, and *high tech intensity*, we use data from the Swiss business census on employment and firms' industry affiliation. Third, to measure the innovation effects, we use patent data, a common indicator to estimate innovation effects of higher education institutions with STEM specialization (e.g. Anselin et al. 1997; Jaffe 1989; Varga 2000).

Applying difference-in-differences (DiD) methods, we show that *labor market size*, *labor market density*, and *high tech intensity* significantly and positively affect innovation effects of newly established UASs. Regarding the relative importance of each economic precondition, we find that *labor market size*, i.e., the total employment in a treated municipality, is the most important factor driving regional heterogeneity, giving some evidence that agglomeration economies might happen through a large enough local labor market that productively absorbs UAS graduates.

This paper is structured as follows. Section 2 reviews the relevant literature and formulates the hypotheses. Section 3 discusses the institutional background of the establishment of UASs. Section 4 covers the explanatory variables, data and some descriptive statistics. Section 5 explains the identification and the empirical strategies. Section 6 presents the results, further analyses and some robustness tests. Section 7 concludes.

2 Related literature and hypotheses

Ever since Jaffe's (1986) classic study, which found a significant association between academic university research and firms' patenting activity, researchers have continued to study the regional coexistence of universities and innovation (Acs et al. 1992, 1994; Anselin et al. 1997; Jaffe 1989; Kim et al. 2005; Link and Rees 1990; Varga 2000). A review of the existing literature by Ghinamo (2012), however, summarizes a number of caveats to consider concerning the (external) validity of the above cited findings, as follows: (1) the identification of the causal effects of higher education institutions on regional innovation is difficult, (2) the sizes of such potential innovation effects are heterogeneous across countries,[1] (3) the type of research (e.g., basic vs. applied) is crucial and (4) not accounting for agglomeration economies could confound the results.

2.1 Innovation effects of higher education institutions

Recent studies in the field of the economics of science and technology are able to address the first caveat by identifying the causal effects of higher education institutions on innovation. These studies do so by means of using natural experiments in the form of the establishment of new institutions to identify treatment effects.[2] Using the establishment of new universities in Italy, Cowan and Zinovyeva (2013) show that these new institutions increased the regional innovation activity (measured by filed patents) within 5 years by 7%. The authors also investigate some effect heterogeneity by splitting their sample in half with respect to the per capita income, level of R&D and level of education. They find evidence for a catch-up process; i.e., regions with low per capita income, a low level of R&D, and a low level of education experience higher innovation effects.

Analyzing the establishment of new engineering universities in Finland and exploiting the subsequent increase in the probability for individuals to graduate with engineering degrees, Toivanen and Väänänen (2016) identify a positive and causal effect on innovation. They estimate that three new technical universities would result in a 20% increase in the number of patents. An even higher effect, i.e., a 32% increase in patents, has been found by Andrews (2019) for newly established colleges in the US. The estimations considering the channels through which colleges affect innovation reveal that college graduates entering the labor market, faculty research and collaborations are less important for innovation effects from newly established colleges than, for example, migration.[3] The differences in the innovation effect sizes of these different studies also support the argument of country heterogeneity by Ghinamo (2012).

Pfister et al. (2021) cover not only the causality caveat but also the evidence provided by Ghinamo (2012) that the type of research conducted by higher education institutions is crucial. Pfister et al. (2021) analyze the establishment of UASs, i.e., higher education institutions of applied research, in Switzerland and find evidence for a positive effect on innovation.[4] Both the innovation quantity, measured by patent applications, and innovation quality (e.g., citations and claims per patent) increased by 13% and 11%, respectively, in regions where UASs were established. In another study focusing on Switzerland, Arvanitis et al. (2008) find that UASs have, compared with academic universities and other research institutions, an above-average propensity to contribute to positive innovation effects, because they are especially likely to cooperate with the local industry.[5]

[1] Analyzing 78 countries, Valero and Van Reenen (2019) find evidence for heterogeneity in the effects of newly established universities on GDP per capita growth partly explained by increased innovation.

[2] For a survey of this approach, see Card (2001).

[3] Although migration to counties with new colleges is the main channel, opening up colleges still has a net positive effect on the innovation of nearby regions.

[4] The analysis is limited to the German speaking part of Switzerland (approximately 65% of all Swiss municipalities).

[5] Toner (2010), more generally, finds that vocational education and training institutions are particularly suited to the role of technology diffusion and, hence, contribute to innovation.

2.2 Innovation and agglomeration economies

The remaining caveat by Ghinamo (2012), i.e., the presence of agglomeration economies—benefits that arise from the grouping of individuals or firms in cities or industrial clusters (Glaeser 2010)—dates back as far as Marshall (1890) and was again raised by Jacobs (1969). Both authors argue that innovation effects, in general, depend on the size and the structure of the regional economy. The new economic geography literature brings forward the argument that innovation effects from higher education institutions can also be affected by agglomeration economies (e.g. Keilbach 2000). Following the taxonomy of Duranton and Puga (2004), three theoretical explanations of agglomeration economies exist, which are all relevant in the context of innovation effects (Carlino and Kerr 2015); they are matching, learning and sharing.

The first explanation for agglomeration economies, i.e., matching, is the improvement of quality and the lowering of costs of labor market matches when more individuals are involved in the market, i.e., when there is a large local labor market (Gerlach et al. 2009).[6] Highly populated regional areas, thus, show higher innovation rates than regions with smaller populations (O'Huallachain 2002). However, this finding seems to be limited to new technological fields, i.e., radical innovations, whereas less populated regions are able to keep pace in mature technological fields, i.e., incremental innovations (Orlando and Verba 2005).

The second explanation for agglomeration economies, i.e., learning, encompasses knowledge spillovers within a region in a narrow sense; a high local density of firms and individuals in a city eases the transmission of tacit, i.e., noncodified, knowledge (Duranton and Puga 2004). While from a theoretical point of view, the underlying mechanism is not well described (for an exception see Glaeser 1999), a vast number of empirical studies show the existence of knowledge spillovers leading to innovation (for reviews see Audretsch and Feldman 2004; Carlino and Kerr 2015).[7] For instance, the probability that patents cite other patents is higher, when the to be cited paper is from the same metropolitan area than another technologically comparable patent (e.g., Jaffe et al. 1993; Murata et al. 2014; Thompson 2006), thus giving evidence for localized knowledge spillovers. Furthermore, Carlino et al. (2007) argue that the easier transmission of tacit knowledge (i.e., learning) is a possible explanation for their finding that employment density, measured by jobs per square mile, is positively associated with patenting activity.

The third explanation for agglomeration economies, i.e., sharing, refers to local specialized inputs needed for innovation, such as high-skilled workers, business services (e.g., patent attorneys, venture capitalists, laboratories for product testing) or upstream producers of high tech input goods (Carlino and Kerr 2015). The theoretical argument behind sharing is that the clustering of industries allows for clustering of specialized inputs and, thus, economies of scale in the economic infrastructure shared by the firms in the downstream industry. This, in turn, leads to lower costs for and a faster implementation of innovations (Duranton and Puga 2004). In particular, the *high tech intensity* of a region has been shown to foster innovation effects from universities (Akhvlediani and Cieślik 2017). Feldman

[6] Matching was first pointed out in a theoretical way by Helsley and Strange (1990) and was further developed by, e.g., Berliant et al. (2006), Ellison and Glaeser (1997), Glaeser (1998), Helsley and Strange (2002), Strange et al. (2006), and Wheeler (2001).

[7] Knowledge spillovers are not limited to innovation. For example, Moretti (2004) or Liu (2015) show positive effects of knowledge spillovers on productivity.

(1994) finds a positive association of business-services employment and local innovation effects and emphasizes the importance of a well-developed regional economic structure for innovation effects. Sharing also applies to the labor market (i.e., labor market pooling) and helps firms to manage their volatile labor demand (Overman and Puga 2010; Strange et al. 2006) or their special skills requirements (Ellison et al. 2010).

Independent of whether agglomeration economies occur due to matching, learning or sharing, the distance from the potential source of innovation (e.g., a higher education institution) to the source of the agglomeration economies (e.g., a high tech industry cluster) is an important determinant of the overall innovation effect (e.g. Arzaghi and Henderson 2008; Belenzon and Schankerman 2013; Valero and Van Reenen 2019). Ghinamo (2012) finds that the innovation effects of higher education institutions might be underestimated in papers that use broad geographical aggregation levels. For Switzerland, Ruffner and Spescha (2018) find that innovation effects (of firms that cluster together) from labor market pooling (i.e., sharing) work over longer distances (up to 60 km), while learning is especially important for short distances (no more than 1 km). Thus, analyzing innovation effects from newly established higher education institutions should be done at the most disaggregated geographic level possible. In the Swiss case, this corresponds to the municipality, which is the smallest political entity.

2.3 Combining innovation effects and agglomeration economies

Given both the findings from the literature on the economics of science and technology and from the literature on agglomeration economies, it becomes clear that analyzing these innovation effects without taking into account the regional differences might be misleading. Depending on how the regional economic preconditions allow for matching, learning and sharing, the potential innovation effects of higher education institutions could be diluted or reinforced.

An analysis of the interaction between agglomeration economies and innovation effects from universities by Varga (2000) reveals that an academic university alone is not sufficient for local innovation effects. He finds that the concentration of economic activities has a significant effect on the innovation output associated with academic university research spending. Agrawal and Cockburn (2003) provide empirical evidence for the interaction of agglomeration economies in the form of sharing and innovation effects from academic universities. They find that a large R&D intensive firm helps smaller firms to absorb knowledge spillovers from local universities by attracting firms, such as producers of intermediate goods and suppliers of producer services, that are also needed by small firms to innovate.

The interaction between labor market matching and the innovation effects from universities is analyzed by Kantor and Whalley (2014). They find that the innovation effects from universities were between 20% and 100% higher for firms in industries that share a labor market with universities (e.g., high tech industries) than for firms in a technologically more distinct industry. Feldman (1994) and Hausman (2017) argue that the local labor market needs to be a certain size to keep the graduates from the research institutes in the local labor force. Orlando et al. (2019) find, for the U.S., that innovation is not fostered by academic university master's programs in counties belonging to the bottom tercile with respect to population.[8]

2.4 Hypotheses and research strategy

Considering all these theoretical and empirical findings, it is important to further clarify how innovation effects from higher education institutions are affected by agglomeration economies. Therefore, we hypothesize that agglomeration economies lead to higher innovation effects from UASs in municipalities that potentially profit from the matching, learning or sharing mechanisms. The theoretical concepts behind these three mechanisms of agglomeration economies thereby correspond to our measures of *labor market size*, *labor market density* and *high tech intensity*. However, answering the question regarding which of these three mechanisms of agglomeration economies is the most important—our second aim of this paper—remains an empirical exercise.

We investigate our hypotheses by analyzing the innovation effects from newly established higher education institutions of applied research—the UASs—at the municipality level. Thereby, we jointly address some of the mentioned caveats. First, the quasi-random establishment of UASs allow us to identify the effects of higher education institutions on innovation. Second, taking the economic preconditions of a municipality into account, we analyze the interaction of this innovation effect with agglomeration economies. Third, the UASs teach and conduct applied research, which is a type of research that is under-investigated (compared to basic research) in the existing literature.

3 A policy reform fostering applied research

In the mid-1990s, the Swiss federal government launched a policy reform targeted at establishing a new type of higher education institute—the UASs. These UASs provide a wide range of fields of study, i.e., from architecture and business through applied psychology and arts to engineering, IT and the life sciences. We focus on campuses for engineering, IT and the life sciences, i.e., campuses with STEM fields, because they have a higher probability of affecting innovation, which is our outcome of interest.

The aim of the reform leading, inter alia, to the establishment of these UASs between 1997 and 2003 was twofold. First, it should increase the prospects for higher education among individuals who had earned a vocational education and training (VET) diploma by allowing them to obtain a bachelor's degree from a UAS. These individuals would thus earn a degree that is different from but equivalent to a bachelor's degree from an academic university. The implementation of this new degree constituted a higher education expansion without diluting the quality of higher education overall, leading to a labor force that is more human-capital intensive than before the reform (Wolter 2017). Second, the mandate of the newly established UASs oblige them to conduct applied research, in collaboration with and on behalf of the regional economy (Bundesrat 1994). The establishment of UASs, thus, led to a strong increase in research and development (R&D) spending by the UASs,

[8] However, somewhat surprising, both master's and PhD programs do not foster innovation in the largest counties with 2 to 18 million inhabitants, either.

i.e., from 100 million CHF (108 million USD) in 2000 to 550 million CHF (593 million USD in 2013 (Lepori and Müller 2016).[9]

While both the increased human-capital stock and the growth in R&D spending are expected to positively affect innovation, Pfister et al. (2021) argue that the establishment process of the UASs happened in a quasi-random manner and was thus most likely unrelated to innovation activities.[10] The authors base their analysis on an extensive reconstruction of the history of each UAS campus—a single UAS can consist of multiple campuses—in the German speaking part of Switzerland. We add to their work by investigating the establishment process in the remaining parts of Switzerland (i.e., the French and Italian speaking parts),[11] by using reports provided by UASs, government offices, associations, articles in newspapers, legal processes and regulations.

In general, the analysis of all these contemporary documents shows that political considerations within and across all three legal layers in Switzerland (i.e., federal, cantonal and municipal[12]) were the driving forces behind the location decisions, not the considerations of how to increase innovation in certain regions.

In the Italian speaking parts of the country, as in the German speaking part, the former professional education and training (PET) colleges—institutions offering 'short-cycle tertiary education' (ISCED 5B) in STEM—were integrated into the UASs established in 1997 (EFHK 2000, 2002). However, a UAS is a different type of institution and UASs are also ranked higher than the former PET colleges, because UASs provide graduates with a 'bachelor or equivalent' (ISCED 6). Thus, the establishment of UASs still constitutes a higher education expansion, even though it sometimes upgraded an already existing campus.

The establishment process in the French speaking part of the country was more difficult. Deviating from their initial declaration to integrate all former PET colleges into one UAS with different campuses but a common strategy for the entire French speaking part, some PET colleges were first only restructured into units mainly operated by the different cantons. The campuses themselves had argued that the strong collaboration with the local economy prevented the reduction and consolidation of campuses and study programs (EFHK 2000, 2002). After heated debates and negotiations across cantons and across campuses, and after shutting down some of the former PET colleges, six UASs were established between 1997 and 2002 in the French speaking part of the country, though two of them were closed down again in 2011 and replaced by a UAS at a new location.

In total, 22 UAS campuses where STEM fields are taught existed between 1997 and 2008. We end our analysis in 2008 because the then introduced master's degree programs at the UASs may distort our results by leading to additional innovation effects not directly linked to the UAS establishment. Figure 1 shows the location of all 22 UASs in 2003. Before and after 2003, there were fewer UASs because they were either not established yet or closed down again, respectively, as discussed above.[13] The data on UAS campuses

[9] Conversion by the exchange rate as of 2013: 1 CHF = 1.079 USD.

[10] For an in-depth analysis of the establishment process see Pfister (2017).

[11] In addition to the German speaking part, which corresponds to 65% of the Swiss municipalities and 72% of the population (in 2000), Switzerland also has a French speaking part (29% of all municipalities and 23% of the population) and an Italian speaking part (6% of the municipalities and 5% of the population).

[12] The Swiss federal state consists of 26 different cantons, the political layer between federal state and municipalities, comparable to, e.g., US states.

[13] Table 4 in Appendix 1 summarizes the timing and location of all STEM campuses of UASs established between 1997 and 2008 in Switzerland.

indicated by a triangle in Fig. 1 are newly collected compared to the analysis by Pfister et al. (2021).

4 Data, variables, and descriptive statistics

To investigate our hypothesis, we merge data from three different datasets. The first is the data on the timing and the locations of the establishment of UASs. We augmented the data of Pfister et al. (2021) by adding data on the UAS establishment in the French and Italian speaking parts (c.f. Sect. 3). This dataset also provides us with the necessary data for defining our treatment (i.e., within a 25 km radius around a UAS) and control groups (i.e., outside a 25 km radius around a UAS). The second is the data on economic preconditions from the business census provided by the Swiss federal statistical office (SFSO). The third is the data on innovation, as measured by patent priority filings, from the European Patent Office (EPO). The patent data is used to construct the dependent variable.

We use the data on the establishment of UASs discussed in Sect. 3 to define the treatment and control groups. We assign municipalities to the treatment group if they are within a 25 km radius of a UAS (actual travel distance). These 25 km distances correspond to the maximum commuting distance of more than 90% of the Swiss labor force (Pfister et al. 2021). All other municipalities are included in the control group. Figure 1 depicts the UAS campuses where STEM fields are taught and the resulting treatment and control groups formed from the 2,222 Swiss municipalities.[14]

To measure our three explanatory variables for regional economic preconditions—*labor market size*, *labor market density* and *high tech intensity*—we use the data from the business census, a Swiss survey containing complete information on the number of employees and firms at the municipality level. The dataset is available for 1995, 1998, 2001, 2005 and 2008. Our main interest is to analyze how important the size and structure of the regional economy are prior to the establishment of UASs for the innovation effects of these UASs. Therefore, we use only data from the years 1995 to 1998 (prior to the UAS establishment) to construct the economic preconditions, i.e., our explanatory variables. We, thereby, rely on measures widely used in the literature (e.g. Carlino et al. 2007; Niebuhr et al. 2019; Ruffner and Spescha 2018; Varga 2000) and operationalize them accordingly. First, for *labor market size*, we use the total employment measured in full-time equivalents. Second, for *labor market density*, we divide the total employment by the size of the settlement and urban areas of each municipality measured in hectares.[15] Third, we use the SFSO (2012) definition of high tech industries to calculate the share of high tech employment at the municipality level.[16]

[14] There is a strong time trend towards municipality mergers. Therefore, we have updated all years to the stock of municipalities as of 2018.

[15] The settlement and urban areas are defined as the land use areas that are not classified as agricultural areas, wooded areas or unproductive areas. As data on the settlement and urban areas are continuously collected by the SFSO, the data are from 1992 through 1997, depending on the municipality.

[16] The following industries are aggregated to the high tech sector: manufacture of chemicals and chemical products; manufacture of basic pharmaceutical products and pharmaceutical preparations; manufacture of fabricated metal products except machinery and equipment; manufacture of computer; electronic and optical products, manufacture of electrical equipment; manufacture of machinery and equipment; manufacture of motor vehicles; trailers and semitrailers; other manufacturing.

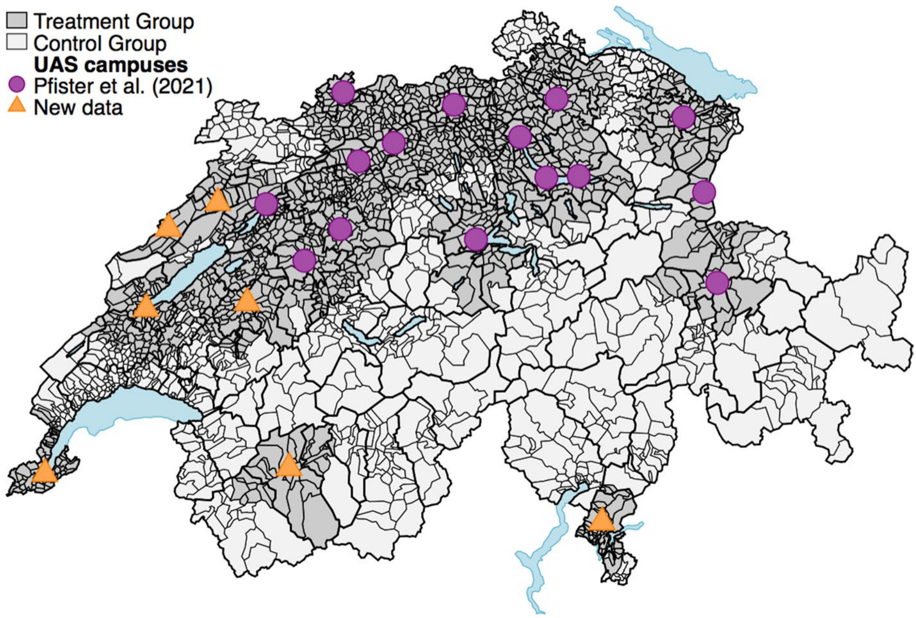


Fig. 1 UAS campuses and treatment and control groups

Having calculated the three measures for economic preconditions, we assign each municipality according to each precondition into one of four quartiles, based on the distribution of both the treatment and control groups. In the case of *labor market size*, this means that quartile I contains all municipalities that belong to the 25% smallest municipalities with respect to *labor market size*, and quartile IV contains all municipalities that correspond to the 25% largest municipalities. Quartiles II and III are defined accordingly. The categorical variable we obtain for each economic precondition and each municipality, reaching from 1 to 4, is the variable we use in our empirical analysis. The reason for that is, we expect the innovation effect of a newly established UAS to be higher in municipalities in higher quartiles in terms of any of the three economic preconditions.

Table 1 shows the descriptive statistics for our three economic preconditions by quartile separately for the treatment and control groups. The comparison of the treatment and control groups reveals no systematic differences between the two groups. The significant difference in *labor market size* in quartile IV is driven by the four largest municipalities in Switzerland that are part of the treatment group. If they are excluded from the sample, the difference between the two groups vanishes without changing the results of the subsequent analysis. Table 1 also makes clear that the majority of Swiss municipalities are small in size.

To construct our dependent variable, which is a proxy for innovation, we use the PATSTAT Worldwide Patent Statistical Database—April 2013 Version—which is publicly available from the EPO. Our dataset covers the years 1990 through 2010. The data comprise the application date and the addresses of the patent applicants and inventors. We exploit all patent applications (more than 300,000) that have at least one applicant address

Table 1 Economic preconditions by quartiles and treatment and control groups

	Full sample										Two sample *t* test
	Treatment group					Control group					
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	
Labor market size (Total employment)											
Quartile I	328	41	24	0.00	85	228	40	25	0.00	84	
Quartile II	354	163	58	85	282	201	172	56	85	282	
Quartile III	366	531	170	283	881	190	518	168	285	873	
Quartile IV	395	5262	17,649	887	270,368	160	3498	6338	886	72,294	*
Labor market density (Total employment per hectare)											
Quartile I	318	1.13	0.45	0.00	1.79	238	1.08	0.44	0.00	1.79	
Quartile II	344	2.60	0.51	1.79	3.56	211	2.57	0.48	1.79	3.54	
Quartile III	369	5.03	0.96	3.57	6.88	187	4.97	0.98	3.57	6.88	
Quartile IV	412	13.13	8.14	6.89	76.84	143	12.76	6.84	6.89	46.16	
High tech intensity (Share of high-tech employment in %)											
Quartile I	288	0.22	0.34	0	1.07	268	0.23	0.34	0	1.07	
Quartile II	355	3.11	1.27	1.07	5.59	200	2.89	1.31	1.08	5.59	*
Quartile III	400	9.98	2.81	5.61	15.81	156	9.89	2.85	5.64	15.78	
Quartile IV	400	31.77	15.21	15.84	87.12	155	31.83	15.29	15.88	97.25	

The economic preconditions are calculated based on the average of the waves from 1995 and 1998 of the SFSO business census. Quartiles are formed for each economic precondition separately but using all municipalities. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

in Switzerland.[17] We link the patent applications to the respective patent priority filing, i.e., the date of the first patent application within a particular patent family (more than 80,000).[18] We then localize the patent priority filings' geographic origin by extracting the ZIP code of the applicant's address and match each ZIP code to the corresponding municipality.[19] We, thereby, use fractional weights for those patent priority filings with patent applicants in different municipalities. In so doing, we follow Pfister et al. (2021), who proceeded equally.

Table 2 shows the descriptive information for our innovation measure, i.e., the number of priority filings per municipality and year, and makes clear that there are differences in the levels of priority filings between the treatment and the control group. In the period before the UASs were established (1990–1997), the municipalities in the treatment group had, on average, 1.78 priority filings per year, while the municipalities in the control group only had 0.74 priority filings. However, these significant differences in levels do not undermine our claim that the treatment and control groups are similar with respect to the growth of patent priority filings over time. The lower part of Table 2 shows the average yearly change in the absolute number of patent priority filings per municipality. In both the pretreatment and the posttreatment period, the treatment and control groups have

[17] Where the applicant address is missing, we resort to the inventors' address.

[18] A patent family is " [...] a collection of patent applications covering the same or similar technical content" (EPO 2017).

[19] Again, we use the inventor's address in cases where information on the applicant address is missing.

Table 2 Number of patent priority filings before and after treatment for the treatment and control groups

	Treatment group					Control group					Two sample *t* test
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	
Mean yearly number of patent priority filings per municipality											
Pretreatment	11,544	1.78	14.36	0	503	6,232	0.74	3.92	0	102	***
Posttreatment	15,873	2.76	20.31	0	786	8,569	1.21	6.37	0	137	***
Mean yearly change in the number of patent priority filings per municipality											
Pretreatment	10,101	0.10	2.66	-77	74	5,453	0.05	1.64	-28	28	
Posttreatment	15,873	0.06	4.01	-266	93	8,569	0.03	2.20	-50	42	

The pretreatment values correspond to the averages of the years 1990–1997, and the posttreatment values correspond to the average of the years 1998–2008 using data from the EPO. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

similar yearly changes in the absolute number of patent priority filings. Thus, the descriptive analysis does not provide evidence for a positive innovation effect of the establishment of UASs, at least not irrespective of the economic preconditions.

Figure 2 gives some descriptive evidence for the existence of coagglomeration of innovation activities and *labor market size* and *labor market density*. Moving rightward along the x-axis, the municipalities in higher percentiles with respect to *labor market size* and *labor market density* show higher positive yearly changes in the number of patent priority filings (y-axis). This relationship becomes especially clear when reaching the top 25% of municipalities of the particular economic preconditions' distribution. However, for *high tech intensity*, this relationship seems not to hold. Innovation also occurs in the municipalities in the lower parts of the *high tech intensity* distribution, giving some indication that *high tech intensity* might not only foster the innovation effects of UASs in the highest quartile of the distribution.

5 Identification and empirical strategy

To investigate how the economic preconditions affect the innovation effects of the newly established UASs, we run three different regression estimations. First, a DiD approach is used, where we include an interaction term for the municipalities' economic precondition to allow for heterogeneity in the innovation effects. In this first specification, we assume a 3-year lag for the treatment. This is following previous literature that lags the treatment by the duration of the educational program (e.g. Andersson et al. 2009; Che and Zhang 2018; Pfister et al. 2021). For Switzerland, the 3-year period corresponds to the normal duration of a bachelor's degree program.

Second, we analyze the evolution of the treatment effect over time. Thereby, we also address the still ongoing debate on the time lags of public policies needed to translate into innovation. According to Azoulay et al. (2019), little is known on the true time lags because many studies use pre-specified lag structures. The authors, however, provide insights for the life sciences industry, by showing that public R&D funding impacts private-sector patents most strongly between 7 and 12 years after being granted. Pfister et al. (2021), using similar data as we do, find a 6-year lag for the first innovation effects of UASs to evolve.

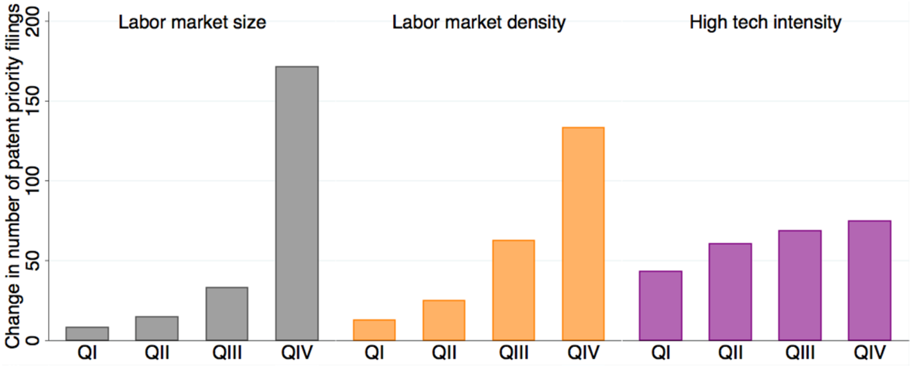


Fig. 2 Distribution of average yearly changes in patent priority filings over economic preconditions. *Notes* The figure shows the change in the number of patent priority filings for each economic precondition and quartile. The change in the number of patent priority filings is calculated for each year within each quartile and is then averaged over all years.

By running a regression analysis in the style of Granger (1969), without pre-specifying a lag, we investigate the time needed for the innovation effect to occur and its further development over time. The analysis thereby also allows to verify our assumption of a 3-year lag in the DiD approach.

Third, we analyze the variation of the innovation effect attributable to the different economic preconditions by means of a DiD approach with interactions for all economic preconditions. However, first, we have to investigate the common trends assumption, which is the crucial element of the DiD approach (Angrist and Pischke 2009).

5.1 Identification

The parallel trends assumption states that the patenting activities would have followed the same trends in the treatment and control groups had the UASs not been established. While this assumption cannot be tested directly, we can exploit the data on innovation in the pre-treatment period to determine whether the two groups shared common trends before the UASs were established. Therefore, we run the following regressions for each economic precondition separately with the natural log of the number of patent priority filings as our dependent variable:[20]

[20] To transform the number of patent priority filings into logs, we follow, e.g., Pfister et al. (2021) and Ruffner and Spescha (2018) and add a constant of 1 to each municipality to avoid missing values in the case of municipalities without patents.

$$
\begin{aligned}
ln(\text{patent priority filings}_{imt} + 1) = \alpha + \beta \text{treatment group}_i + \tau_t + \sum_{k=2}^{4} \lambda_k \text{precondition}_{ik} \\
+ \theta_t * \text{treatment group}_i * \tau_t \\
+ \sum_{k=2}^{4} \kappa_k \text{treatment group}_i * \text{precondition}_{ik} \\
+ \sum_{k=2}^{4} \rho_{kt} \text{treatment group}_i * \text{precondition}_{ik} * \tau_t + \phi_m + \mu_{imt},
\end{aligned}
\tag{1}
$$

with i=municipality $\in$ [1, 2,222], t=year $\in$ [1990,2000], m=regional labor market $\in$ [1,106] and μ_{imt}=$\nu_m + \eta_{imt}$.

The regression coefficients of interest in Eq. (1) are the θ_t and ρ_{kt}, which indicate treatment group specific time trends and show whether the potential treatment group specific time trends vary along the dimension of economic preconditions, respectively. If all these regression coefficients are insignificant and small, we have strong support for our assumption of parallel trends.

Although the first UASs were already established in 1997, the pretreatment period that we analyze is the years 1990 through 2000. The reason for choosing this time period is that we assume a three year lag—corresponding to the average duration of a bachelor program (Pfister et al. 2021)—for the first innovation effects from UASs to occur, and therefore, the trends of innovation activities in the treatment and control groups should also remain parallel up to 3 years after the establishment of the first UASs.

Table 3 summarizes the results of the three regressions of log patent priority filings on *labor market size*, *labor market density* and *high tech* intensity as shown in Eq. (1). For each precondition and quartile, it shows the treatment group specific time trend that is small and insignificant for all quartiles.[21]

5.2 Empirical strategy

To analyze how economic preconditions affect innovation effects from UASs, we use a DiD approach and extend it by including interaction terms for the quartile a municipality belongs to with respect to *labor market size*, *labor market density* and *high tech intensity*. With this specification, we focus on the importance of each precondition individually and estimate the following equation separately for the outcome variable, i.e., the natural log of the number of patent priority filings:

[21] Further analyses of the parallel trends assumption (graphically and empirically) are provided in Appendix 2.

Table 3 Parallel trends: estimated marginal effects for the treatment group per year and quartile

	Labor market size	Labor market density	High tech intensity		Labor market size	Labor market density	High tech intensity
1991				*1996*			
Q1	− 0.0260	− 0.0285	− 0.0165	Q1	0.0100	0.0036	− 0.0097
	(0.0166)	(0.0131)	(0.0203)		(0.0234)	(0.0248)	(0.0271)
Q2	0.0158	0.0284	0.0140	Q2	0.0367	0.0731**	0.0977***
	(0.0198)	(0.0228)	(0.0265)		(0.0336)	(0.0280)	(0.0358)
Q3	0.0078	− 0.0424	0.0007	Q3	0.0997**	0.0304	− 0.0397
	(0.0282)	(0.0325)	(0.0380)		(0.0447)	(0.0571)	(0.0485)
Q4	− 0.0400	0.0027	− 0.0441	Q4	− 0.0654	− 0.0521	0.0168
	(0.0575)	(0.0624)	(0.0564)		(0.0687)	(0.0727)	(0.0586)
1992				*1997*			
Q1	− 0.0072	− 0.0040	0.0154	Q1	− 0.0160	− 0.0259**	− 0.0054
	(0.0183)	(0.0153)	(0.0195)		(0.0286)	(0.0235)	(0.0308)
Q2	0.0020	− 0.0063	0.0074	Q2	0.0440	0.0581*	0.0826**
	(0.0250)	(0.0244)	(0.0304)		(0.0298)	(0.0324)	(0.0358)
Q3	0.0208	0.0367	0.0161	Q3	0.0511	0.0228	− 0.0657
	(0.0395)	(0.0412)	(0.0389)		(0.0518)	(0.0618)	(0.0440)
Q4	0.0612	0.0422	0.0123	Q4	− 0.0653	− 0.0630	− 0.0393
	(0.0495)	(0.0548)	(0.0448)		(0.0659)	(0.0690)	(0.0616)
1993				*1998*			
Q1	0.0034	0.0006	0.0172	Q1	0.0093	0.0081	− 0.0013
	(0.0164)	(0.0193)	(0.0251)		(0.0217)	(0.0223)	(0.0271)
Q2	0.0426	0.0572*	0.0328	Q2	0.0315	0.0442	0.0656
	(0.0302)	(0.0310)	(0.0341)		(0.0325)	(0.0323)	(0.0404)
Q3	0.0008	− 0.0112	0.0052	Q3	0.0800*	0.0761	0.0674
	(0.0441)	(0.0476)	(0.0474)		(0.0462)	(0.0535)	(0.0453)

Table 3 (continued)

	Labor market size	Labor market density	High tech intensity		Labor market size	Labor market density	High tech intensity
Q4	0.0254	0.0117	− 0.0056	Q4	0.0634	0.0238	0.0403
	(0.0549)	(0.0589)	(0.0553)		(0.0680)	(0.0746)	(0.0549)
1994				*1999*			
Q1	− 0.0067	− 0.0162	− 0.0125	Q1	0.0001	− 0.0171	− 0.0058
	(0.0199)	(0.0225)	(0.0249)		(0.0226)	(0.0248)	(0.0317)
Q2	− 0.0026	− 0.0164	0.0048	Q2	0.0093	0.0253	0.0252
	(0.0314)	(0.0312)	(0.0364)		(0.0318)	(0.0351)	(0.0391)
Q3	0.0149	0.0002	− 0.0155	Q3	− 0.0235	− 0.0465	− 0.0371
	(0.0413)	(0.0460)	(0.0426)		(0.0459)	(0.0608)	(0.0443)
Q4	− 0.0224	0.0056	− 0.0085	Q4	0.0149	0.0179	− 0.0054
	(0.0614)	(0.0596)	(0.0605)		(0.0740)	(0.0749)	(0.0631)
1995							
Q1	− 0.0007	0.0083	− 0.0034				
	(0.0188)	(0.0193)	(0.0251)				
Q2	0.0412	0.0039	0.0611*				
	(0.0292)	(0.0339)	(0.0317)				
Q3	0.0668	0.0822**	0.0098				
	(0.0422)	(0.0408)	(0.0393)				
Q4	− 0.0135	− 0.0163	0.0208				
	(0.0551)	(0.0613)	(0.0542)				

The results report the marginal effects estimated from the OLS regressions. The full regressions are reported in Appendix 2, Table 5. Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets are included. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

$$
\begin{aligned}
ln(\text{patent priority filings}_{imt} + 1) = {} & \alpha + \beta \text{treatment group}_i + \gamma \text{treatment dummy}_{i(t-3)} \\
& + \sum_{k=2}^{4} \delta_k \text{treatment dummy}_{i(t-3)} * \text{precondition}_{ik} \\
& + \sum_{k=2}^{4} \kappa_k \text{treatment group}_i * \text{precondition}_{ik} \\
& + \sum_{k=2}^{4} \lambda_k \text{precondition}_{ik} + \tau_t + \phi_m + \mu_{imt},
\end{aligned} \tag{2}
$$

with i=municipality $\in [1,2222]$, t=year $\in [1990,2008]$, m=regional labor market $\in [1,106]$ and $\mu_{imt} = v_m + \eta_{imt}$.

Whether or not a municipality belongs to the treatment group is indicated by *treatment group*$_i$. The categorical variable *precondition*$_{ik}$ indicates to which of the four quartiles k a municipality belongs to with respect to the measure for the economic precondition at hand. Since we only include preconditions, the categorical variable *precondition*$_{ik}$ is constant over time (based on the averages of the years 1995 and 1998). The λ_k values, thus, show the association between the economic preconditions and innovation of municipalities, irrespective of the treatment. The interaction of the treatment group dummy with *precondition*$_{ik}$ allows the municipalities in different quartiles of the treatment group to have different initial levels of patent priority filings (κ_k, quartile I is the base group). For the actual treatment, captured by the term *treatment dummy*$_{i(t-3)}$, we assume a 3-year lag, the normal duration of a bachelor's degree program. In so doing, we follow other studies that lag the treatment by the duration of the educational program (e.g., Andersson et al. 2009; Che and Zhang 2018; Pfister et al. 2021).[22] We further include year (τ_t), and regional labor market fixed effects (ϕ_m). μ_{imt} represents the error term.

The coefficients of interest are γ and δ_k. The first coefficient captures the lagged innovation effects of the establishment of a UAS for a municipality in the base group. The coefficients δ_k of the interaction between the *treatment dummy*$_{i(t-3)}$ and the categorical variable *precondition*$_{ik}$ are estimated separately for each of the four quartiles. The resulting coefficients, i.e., δ_2, δ_3 and δ_4, indicate the heterogeneity in the innovation effects due to differences in the economic preconditions.

We include the labor market regions' fixed effects in our regressions; therefore, identification comes by comparing the changes over time in the number of patent priority filings of municipalities that are in the same labor market region but in either the control group or the treatment group.[23] Figure 7 in Appendix 2 shows that, over time, there is variation at the labor market region level. In 43% of the in total 106 labor market regions, there exist both municipalities in the treatment and in the control group, and in another 36% of the labor market regions, we have all municipalities belonging to the treatment group, which still allows us to use the variation over time.

To investigate, first, the time needed for a treatment effect to occur, second, its persistence over time and, third, whether our assumption of a 3-year lag for the treatment effect in the DiD is suitable, we run a second set of regressions to analyze the evolution of the

[22] Fukugawa (2013) also assumes a 3-year lag, because this is the time needed to develop research collaborations.

[23] Figure 1 in Sect. 4 indicates the 106 labor market regions with the thicker black lines.

treatment effect over time. In these regressions, we allow for eight leads (i.e., anticipatory effects) and ten lags (i.e., posttreatment effects) as shown in Eq. (3). We chose the number of leads and lags to ensure a sufficient number of observations per period. As we only have few observations for the earliest and latest periods (most UASs were established in 1997 and 1998), we aggregate observations at the beginning and the end of the observational period in bins. Thus, all periods eight or more years before the treatment and all periods ten or more years after the treatment, respectively, are binned. Thereby, we follow a common procedure in the literature on dynamic treatment effects (Abraham and Sun 2020; Borusyak and Jaravel 2017; Schmidheiny and Siegloch 2020).

$$\begin{aligned} ln(\text{patent priority filings}_{imt}+1) = \alpha + \beta \text{treatment group}_i & \\ + \delta_{\underline{g}} \sum_{\rho<-7} \text{treatment dummy}_{it}^{\rho} & \\ + \sum_{\rho=-7}^{-2} \delta_{\rho} \text{treatment dummy}_{it}^{\rho} & \\ + \sum_{\rho=0}^{9} \delta_{\rho} \text{treatment dummy}_{it}^{\rho} & \\ + \delta_{\overline{g}} \sum_{\rho>9} \text{treatment dummy}_{it}^{\rho} & \\ + \tau_t + \phi_m + \mu_{imt}, & \end{aligned} \tag{3}$$

where i, t, m and μ_{imt} are defined as in Eq. (2) and $\rho = t - E_i$ with E_i being the initial time of treatment for unit i. The two bins at the beginning and end of the observational period contain the following periods $\underline{g} = [-13, -7)$ and $\overline{g}$=(9,11], respectively. The base year of the regression is the year before the treatment, i.e., $\rho = t - E_i = 1$.

Equation (3) differs from Eq. (2) in the following two ways. First, we do not include economic preconditions since we run the regression on subsamples built along the lines of the quartiles of each economic precondition; second, the pretreatment and posttreatment dummies indicate the years before and after the treatment takes place. For a municipality that is, for example, first treated in 2001, in the year 2008, the posttreatment dummy with $\rho = 7$ would switch to one. The δ_ρ with $\rho < 0$ then indicate whether there are some anticipatory effects and the δ_ρ with $\rho \geq 0$ show how the treatment effect evolves over time (both conditional on the regional labor market and year effects).

To analyze the relative importance of the different economic preconditions, we run a third specification, i.e., a DiD estimation that includes all three preconditions as depicted in Eq. (4):

$$
\begin{aligned}
ln(\text{patent priority filings}_{imt}+1) = {} & \alpha + \beta \text{treatment group}_i + \gamma \text{treatment dummy}_{i(t-3)} \\
& + \sum_{p=1}^{3}\sum_{k=2}^{4} \delta_{kp} \text{treatment dummy}_{i(t-3)} * \text{precondition}_{ikp} \\
& + \sum_{p=1}^{3}\sum_{k=2}^{4} \kappa_{kp} \text{treatment group}_i * \text{precondition}_{ikp} \\
& + \sum_{p=1}^{3}\sum_{k=2}^{4} \lambda_{kp} \text{precondition}_{ikp} + \tau_t + \phi_m + \mu_{imt},
\end{aligned}
\tag{4}
$$

where i, t, m, k and μ_{imt} are defined as in Eq. (2) and $p = 1$ is *labor market size*, $p = 2$ is *labor market density* and $p = 3$ is *high tech intensity*.

Compared to Eq. (2), the only difference is the subscript p, which indicates the inclusion of the $p = 3$ different preconditions, i.e., *labor market size*, *labor market density* and *high tech intensity* at the same time. The interactions between the $\textit{treatment dummy}_{i,t-3}$ and $\textit{precondition quartile}_{ikp}$ show how the innovation effects (associated with the establishment of UASs) vary among municipalities with different levels of the three economic preconditions. By including all economic preconditions at the same time, we are able to measure whether the innovation effect more likely appears with, e.g., the precondition *labor market size* or the precondition *high tech intensity*.

Instead of directly interpreting the estimation results of Eq. (4), we use the estimation results to quantify the variation in the innovation effect (associated with the establishment of UASs) explained by each precondition. In other words, we focus on how the innovation effect varies across municipalities with different economic preconditions, i.e., *labor market size*, *labor market density* and *high tech intensity*, thereby quantifying their relative importance for innovation effects from UASs.

To quantify the variation of the innovation effect attributable to the different economic preconditions, we first calculate the variance of the sample estimates δ_{kp} for the interaction between the economic precondition a municipality belongs to and the treatment variable, within each precondition p, to obtain $Var(size)$, $Var(density)$ and $Var(intensity)$.[24] We then sum up these variances and—by dividing the variance of each precondition by the total variance of the innovation effect associated with UASs—report the shares of the variance in the total innovation effect associated with UASs, attributable to *labor market size*, *labor market density* and *high tech intensity*.

[24] We use the respective sample analogues to calculate the variances. For $Var(size)$, we use the coefficients $\delta_{k,size}$ of the interaction between the economic precondition of a municipality and the treatment variable and calculate $Var(size) = \frac{1}{n_T-1}\sum_{i=1}^{n}\sum_{t=1990}^{2008}\sum_{k=1}^{4} \textit{treatment dummy}_{i(t-3)} * \textit{precondition}_{ik,size} * (\hat{\delta}_{k,size} - \bar{\delta}_{size})^2$, with $n_T \equiv \sum_{i=1}^{n}\sum_{t=1990}^{2008} \textit{treatment dummy}_{i,t-3}$, which represents all the municipality-year observations where a UAS was nearby. $\hat{\delta}_{k,size}$ is the sample estimate for the treatment effect in quartile k with respect to the *labor market size* and $\bar{\delta}_{size} \equiv \frac{1}{n_T}\sum_{i=1}^{n}\sum_{t=1990}^{2008}\sum_{k=1}^{4} \delta_{k,size} * \textit{treatment dummy}_{i,t-3} * \textit{precondition}_{ik,size}$. We analogously calculate the respective variances for the *labor market density* and *high tech intensity*.

6 Results

According to our empirical strategy outlined in Sect. 5.2, we report the results from (1) the DiD approach extended by an interaction term for a single economic precondition, (2) the analysis of the evolution of the treatment effect over time and (3) the relative importance of each economic precondition for the variance of the estimated innovation effect associated with the establishment of UASs.

To investigate the importance of each economic precondition for innovation effects from UASs separately, we first report the results of the estimation of Eq. (2). Figure 3 therefore depicts the coefficients of interest for the regressions of log patent priority filings on (a), *labor market size* (b) *labor market density* and (c) *high tech intensity*.[25] On the left hand side of the graphs, the reported total treatment effects reflect a comparison to a nontreated municipality in the same quartile with respect to the economic precondition at hand. The estimated coefficients, thus, show whether a nearby established UAS led to higher innovation activities in the different quartiles. On the right-hand side, we compare the treatment effect for a municipality in a certain quartile to the treatment effect for municipalities in quartile I that also belong to the treatment group. The estimated coefficients in this case reflect the heterogeneity of the treatment effect due to economic preconditions within the treatment group.

Focusing on the left-hand side of Fig. 3 reveals that the establishment of UASs lead on average to significantly higher innovation activities in municipalities belonging to quartile IV either with respect to *labor market size*, *labor market density* or *high tech intensity*. An example: a treated municipality in quartile IV in terms of its *labor market size* has a patenting activity that is 0.16 or 17% higher, respectively, than in a nontreated municipality in quartile IV.[26] Overall, for municipalities in lower quartiles, the total effect of the UAS establishment on patenting activity is not positive and significantly different from zero, except for municipalities in quartile III with regard to *high tech intensity*. However, in quartile I and quartile II for *labor market size* and in quartile I for *labor market density*, the UAS establishment led to a small decrease in patenting activity. Although, since the number of patent priority filings in municipalities in quartile I are very low, the percentage decline translates into an absolute decline in patenting activity that is near zero.

The right-hand side of Fig. 3 makes clear that the treatment effects compared within the treatment group are slightly higher than when compared across the treatment and control groups, because smaller municipalities tend to show a small, though insignificant, treatment effect. Independent of the economic precondition, the municipalities in quartile IV, and for *labor market size* and *high tech intensity* also municipalities in quartile III, profit significantly more from a nearby UAS than the treated municipalities in quartile I. For *labor market size* and *labor market density*, the treatment effect is also significantly higher compared to quartile III, which gives evidence that municipalities with labor markets in the uppermost quarter of the distribution with respect to size and density, profit more from a nearby UAS than the other treated municipalities. Municipalities with an above median *high tech intensity* also seem to profit significantly from a nearby UAS compared to the treated municipalities in the lower part of the distribution.

Both the comparison across the treatment and the control groups, as well as the comparison within the treatment group gives some evidence for a certain critical value in economic

[25] Table 6 in Appendix 3 shows the regression table for all three DiD estimations.

[26] The treatment effect in percentage is calculated as follows: $(exp^{0.16} - 1) * 100 = 17\%$.

preconditions that is needed for innovation effects from a nearby UAS to occur. Relying upon our classification into quartiles, a municipality needs, on average, at least approximately 900 employees, 7 employees per hectare (the minimums in quartile IV) or 6% of employees in high-tech industries (the minimum in quartile III) to profit from a nearby UAS. These results are in line with our hypothesis and with the existence of agglomeration economies that foster innovation from a nearby UAS through improved matching, sharing and learning.

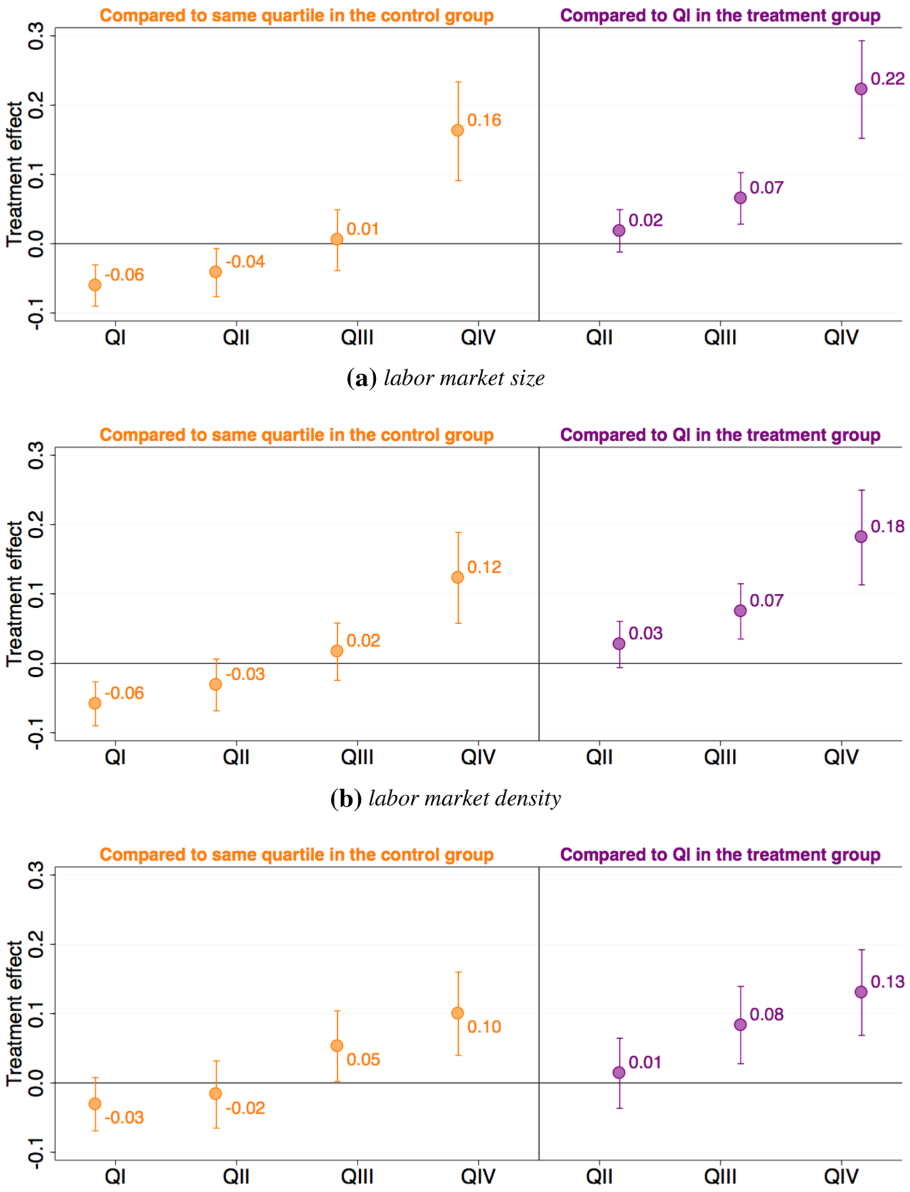
The results of our second analysis, i.e., on the evolution of the treatment effect over time, are reported in Fig. 4 with the results on *labor market size* in panel (a), *labor market density* in panel (b) and *high tech intensity* in panel (c). The negative values on the horizontal axis indicate the years before the treatment, individually, for each municipality according to the year of the establishment of the nearby UAS, and the positive values correspond to the years after the treatment. Each panel summarizes the estimation results of four regressions, run separately for each quartile of the economic precondition of interest.

For the pretreatment years, neither of the quartiles of any economic precondition show systematic anticipatory trends, which supports our identification strategy. Indeed, the effects are small and predominantly not significantly different from zero, with the exception of effects in quartile II in periods 8 and 6 before the treatment. However, there is no pattern of pretreatment trends.

In the posttreatment years, however, the pattern for the four quartiles looks different, depending on the economic precondition. For *labor market size*, there is a positive evolution of the treatment effect over time, although only for quartile IV, where the treatment effect starts increasing some 6 years after the establishment of the UASs—and therefore takes longer than we assumed in our DiD approach. The treatment effect then stabilizes at an approximately 10–18% higher patenting activity compared to the control group. The pattern for *labor market density* is comparable to that for *labor market size*, however, effect sizes are not significantly different from zero. The municipalities that are in quartile IV with respect to *high tech intensity*, seem not to profit from a nearby UAS. In contrast, the municipalities in quartile III experience positive, though not statistical significant, innovation effects over the entire poststreatment period. The effects are increasing over time. One possible explanation for the result that effects only increase in quartile III could be that *high tech intensity*, referring to the concept of sharing, is only somewhat beneficial for fostering innovation effects from UASs, because a too strong concentration of high-tech industries suppresses the existence of, for example, the business services needed for innovation.

The analysis of the evolution of treatment effects reveals that for all three economic preconditions, the treatment effect occurs six years after the establishment of a new UAS, at the latest. Therefore, with our assumption of a 3-year lag we err on the side of caution. We thus prefer to use the three year time lag in our DiD, because it follows a standard assumption in the literature. The effect sizes in our DiD estimation, thus, provide a conservative estimate of the innovation effects linked to the UAS establishment.

To analyze the relative importance of the economic preconditions of *labor market size*, *labor market density* and *high tech intensity*—our third specification illustrated in Eq. (4)—we include all preconditions jointly in a DiD estimation. However, we are not interested in the regression coefficients per se but use them to decompose the variance of the estimated

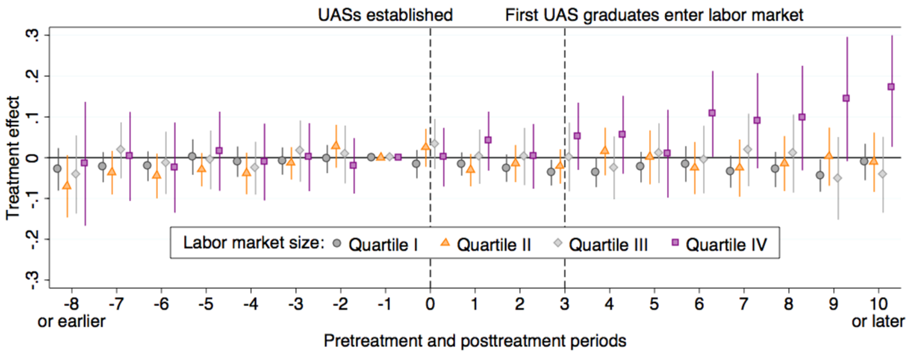


(a) *labor market size*

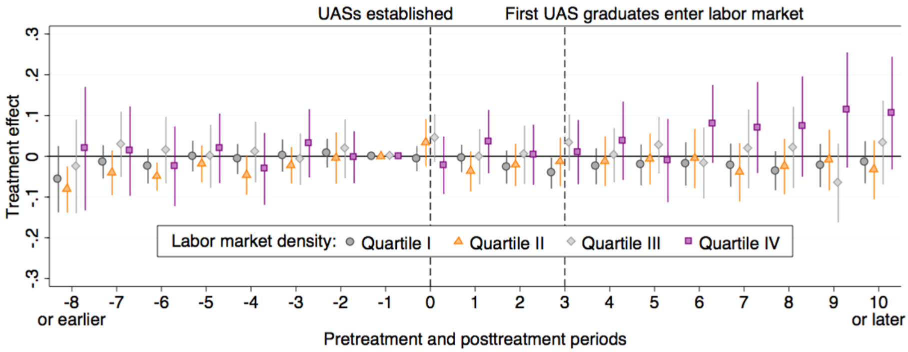
(b) *labor market density*

(c) *high tech intensity*

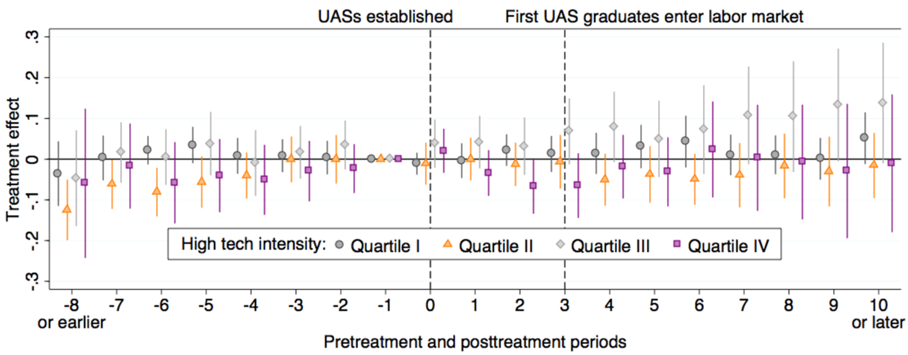
Fig. 3 Treatment effects for municipalities by quartile and economic precondition. *Notes* The figure shows the coefficients from the OLS regressions for *labor market size* in panel **a**, *labor market density* in panel **b** and *high tech intensity* in panel **c**. Dependent variable: ln(patent priority filings + 1). Left-hand side of panels: treatment effects in the treated municipalities relative to the nontreated municipalities in the same quartile, i.e., $\gamma + \delta_k$ from Eq. (2). Right-hand side of panels: treatment effect in the treated municipalities relative to the treated municipalities in quartile I, i.e., δ_k from Eq. (2). The fixed effects for the regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets.



(a) *labor market size*



(b) *labor market density*



(c) *high tech intensity*

Fig. 4 Evolution of treatment effects over time by quartile and economic precondition. *Notes* The figure shows the coefficients from the OLS regressions for *labor market size* in panel **a**, *labor market density* in panel **b** and *high tech intensity* in panel **c**. Dependent variable: ln(patent priority filings + 1). Each panel shows the results for all quartiles (markers' shape). Fixed effects for regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets. Periods 8 years or more before the treatment and 10 years or more after the treatment, respectively, are summarized in bins. The base year of each regression is the last year before the establishment of a UAS. The two vertical lines indicate (1) the period when the UASs are established and (2) the period when the first UAS graduates enter the labor market, corresponding to the 3-year lag we assume in the DID.

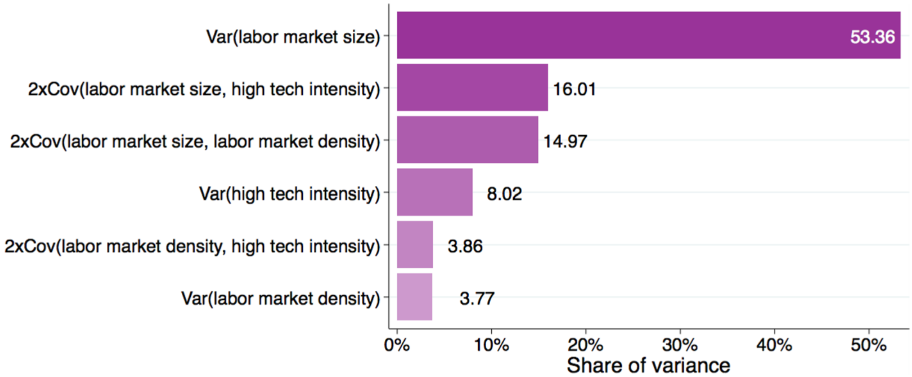


Fig. 5 Variance of the treatment effect explained by economic preconditions. *Notes* The figure shows the share of the variance in the treatment effect, obtained by an OLS regression including all economic preconditions, as in Eq. (4), explained by different economic preconditions. Dependent variable: ln(patent priority filings + 1). We calculate the sample variance as follows: *Var*(Treatment Effect)=*Var*(size)+ *Var*(density)+ *Var*(intensity)+2*Cov*(size,density) +2*Cov*(size,intensity)+2*Cov*(density,intensity).

treatment effect (c.f. Sect. 5.2).[27] The results of the variance decomposition in Fig. 5 quantify the relative importance of the three economic preconditions.[28] The sample variance of the treatment effect attributable to *labor market size* equals 0.0094, which corresponds to 53% of the total sample variance in the treatment effect.

It is, therefore, the most important economic precondition in explaining the variance of the treatment effect, as *labor market density* only explains 4% and *high tech intensity* only explains 8%. Figure 5 also reveals that the combination of *labor market size* with either *labor market density* or *high tech intensity* substantially contributes to the variance in the estimated treatment effect, giving evidence that this combinations might be particularly vital for fostering innovation effects from nearby established UASs.

Overall, the results of the DiD estimations and of the evolution of the treatment effects over time show that with respect to *labor market size* and *labor market density*, only the municipalities in the highest quartile profit significantly from nearby established UASs. In the case of *high tech intensity*, the municipalities in quartile III also profit significantly and, over time, even outperform the municipalities in quartile IV. Moreover, the analysis of the variance of the treatment effect shows that *labor market size* explains the largest share of the innovation effects from UASs, an effect that is even stronger when a municipality with a large labor market also has a high *labor market density* or *high tech intensity*.

6.1 Further analyses and robustness tests

We further analyze the effect of UASs on innovation, by also including quality measures for innovation, instead of only the number of patent priority filings as the quantity measure for innovation. Furthermore, to test the robustness of our results with respect to (1) our definition of the economic preconditions, (2) omitted explanatory variables for innovation differences across regions and, (3) our treatment specification, we run a number of robustness

[27] Table 7 in Appendix 3 nevertheless shows the most important estimation results.

[28] For the absolute values of the variance in the total treatment effect see Table 8 in Appendix 3.

checks. Finally, we address concerns on the exogeneity of the location of the newly established UASs by only exploiting the variation over time in the establishment of UASs, thus, limiting the analysis of heterogeneous innovation effects to the treatment group.

6.1.1 Patent quality measures as additional outcome variables

To analyze whether our results also hold for quality measures for innovation, we rerun our regression in Eq. (2) using the following four patent quality measures, typically used in the literature (Squicciarini et al. 2013): (1) the *grant ratio*, (2) the *citation ratio*, (3) the *claims ratio*, and (4) the *average patent family size*. First, we use the *grant ratio*, i.e., the share of granted patents per total number of patent applications. The *grant ratio* indicates the share of applications that actually fulfill the patentability criteria, i.e., novelty, inventive step and industrial applicability. Fulfilling these criteria is associated with a higher technological and economic value of the patent OECD (2009). Second, we use the forward *citation ratio*, i.e., the number of patent citations per patent family. The number of forward citations a patent receives in the 3 or 5 years following the application, respectively, are a proxy for the economic value of the patented technology (Gambardella et al. 2008).

Third, we investigate the *claims ratio*, i.e., the number of claims in patents in relation to the number of patent families. The *claims ratio* measures the boundaries of the exclusive rights of a patent and, thus, the technological scope of a patent (Squicciarini et al. 2013).[29] Fourth, we analyze the *average patent family size*, i.e., the average number of patents filed in different countries, related to each other by protecting the same invention. The *average patent family size* measures the potential value associated with an innovation (Harhoff et al. 2003). The results of the regressions using patent quality measures are reported in Appendix 4 in Table 9 for *labor market size*, Table 10 for *labor market density* and in Table 11 for *high tech intensity*.

We find similar patterns for patent quality, compared to patent quantity. Municipalities in quartile IV with respect to *labor market size*, *labor market density* and *high tech intensity* profit significantly from a nearby UAS, though, effect sizes are smaller compared to patent quantity.[30] However, in contrast to patent quantity, we find for patent quality that municipalities in quartile III with respect to all economic preconditions also profit significantly from a nearby UAS. Overall, the analyses of the patent quality, thus, confirms, that the increase in patent quantity is not associated with a decrease in patent quality. Therefore, our measure for patent quantity, i.e., the number of patent priority filings, is a valid measure of the positive innovation effects (both in quantity and quality) after the establishment of UASs.

6.1.2 Alternative definition of economic preconditions

To assess the robustness of our results with respect to our definition of economic preconditions, we use alternative measures for the economic preconditions, based on the number of firms in a municipality instead of the total employment. We calculate the *number of firms* (corresponding to labor market size), *firm density* and *high tech firm intensity* of a

[29] As the number of claims in a patent depend on the different patent offices' rules and regulations (Squicciarini et al. 2013), we calculate the measure *patent claims* separately for patent applications at the EPO and the US patent office.

[30] This finding is in line with Pfister et al. (2021).

municipality in accordance to the procedure explained in Sect. 4. The firm-based measures for economic preconditions are then used to rerun our empirical analysis. The regression results of the estimation of Eq. (2) are shown in Fig. 8 in Appendix 5. Both the pattern across quartiles and the size of the coefficients indicate that our reported results, when analyzing each economic precondition separately, are not driven by the definition of these economic preconditions.

The estimation results for the variation of the innovation effect attributable to the different economic preconditions (Eq. 4), depicted in Fig. 9 in Appendix 5 show that it is again the size of the regional economy, this time measured by the *number of firms*, that explains most of the innovation effect after the establishment of UASs (44%).[31] Although, firm-based economic preconditions also explain heterogeneity in innovation effects after the establishment of UASs, we stick to our employment-based measure of economic preconditions, because we assume the labor market to be the most important source of agglomeration economies in connection with the establishment of UASs.[32]

6.1.3 Controlling for further municipality preconditions

To analyze whether there are omitted explanatory variables that drive innovation differences after the establishment of UASs across regions, we include a number of control variables in our DiD specification in Eq. (2). Some control variables may also function as outcome variables in the posttreatment years and could distort the results if included in the regression (Angrist and Pischke 2009). Therefore, we only include municipality characteristics from the pretreatment period that are, thus, stable over time. The data come from the population census in the year 2000.[33]

We include control variables for (1) education, i.e., the share of upper secondary and tertiary educated people in a municipality, (2) the unemployment and the labor force participation rates in percentage of the people in a municipality, (3) the share of foreigners in a municipality (4) the age structure, i.e., the share of individuals between 20 and 64 and above 64, respectively, (5) the number of commuters per 100 inhabitants of a municipality and (6) the type of the municipality, using a classification into nine different types of municipalities.[34]

The results in Appendix 5 for *labor market size* (Table 13), *labor market density* (Table 14) and *high tech intensity* (Table 15) show that including these control variables does not change our results.[35] The results are also robust to the order of the inclusion of

[31] Employment-based and firm-based economic preconditions are strongly correlated. Table 12 in Appendix 5 shows the number of municipalities in each of the four quartiles, when split into quartiles according to either employment-based or firm-based economic preconditions.

[32] A comparison of the R^2 of the regressions of Eq. (4) for the employment-based economic preconditions also reveals, that the employment-based economic preconditions explain slightly more of the total variation ($R^2 = 0.401$) than the regression with firm-based economic preconditions ($R^2 = 0.397$).

[33] In our empirical analysis, we assume a three year lag, so the year 2000 is actually at the beginning of the treatment period. However, as the population census is conducted only every 10 years, using the year 2000 population census data is our preferred option.

[34] The classification is done by the SFSO. The nine types of municipalities are (1) agrarian-mixed municipality, (2) agrarian municipality, (3) high income municipality, (4) industrial and tertiary municipality, (5) rural commuter municipality, (6) periurban municipality (7) suburban municipality (8) touristic municipality and (9) center municipality.

[35] Due to missing data in 98 municipalities, we have to run this robustness analysis on a smaller sample. Therefore, we also report the regression without further control variables in column (1), also with identical results compared to our main specification in Fig. 3.

the control variables and to the inclusion of different subsets of these control variables.[36] These findings give some evidence that our results are not just artifacts of economic or demographic differences across municipalities prior to the establishment of UASs.

6.1.4 Testing the treatment specification

As for our treatment specification, we examine first, whether our results are driven by municipalities at the upper end of the distributions of our measures for economic preconditions, as Fig. 2 reveals that municipalities with strong economic preconditions also tend to have the most patent priority filings. Therefore, we run our regressions in Eq. (2) excluding municipalities in the top deciles with respect to *labor market size*, *labor market density* and *high tech intensity*. For *labor market size* and *labor market density*, the municipalities we exclude from the estimation coincide with the major cities in Switzerland, for *high tech intensity* the excluded municipalities are rather industrial, rural or suburban. In any case, the results shown in Fig. 10 in Appendix 5 remain unaltered as compared to our main findings (c.f. Fig. 3).

Second, we test whether our results are driven by one of our 22 different treatment groups, as they are very heterogeneous with respect to the patenting activity. We do so by excluding one treatment group at a time and then rerun our regression in Eq. (2). We would expect that the results do not change when a treatment group is excluded. Figure 11 in Appendix 5 shows for *labor market size*, that this is actually the case. The treatment effects in each quartile do not differ across the 22 different regressions. We find the same results when analyzing *labor market density* or *high tech intensity*, supporting our expectation that the results are not driven by one particular treatment group.[37]

6.1.5 Addressing exogeneity concerns

To support our identification strategy (Sect. 5.1), we address exogeneity concerns regarding the location of the newly established UASs by focusing only on the treatment group and exploiting the variation in treatment over time to estimate innovation effects. This specification, thus, compares the evolution of innovation activities in treated municipalities to municipalities that have not received the treatment yet. By comparing treated municipalities only, we obviate potential concerns that UASs were established in up-and-coming regions and that, therefore, the comparison between treatment and control groups would be misleading. The DID results of the analyses focusing on treatment groups only are shown in Fig. 12 in Appendix 5. These results are identical to our main analysis, which gives evidence that the effects we identified in the main analysis are not driven by endogeneity in the location of the newly established UASs.

In sum, the robustness tests conducted in Sects. 6.1.2, 6.1.3, 6.1.4 through 6.1.5 show that our main results are robust to (1) alternative definitions of the economic preconditions, (2) the inclusion of further control variables and, (3) different specifications of the

[36] This was tested using the user-written STATA program *checkrob* to run 131,072 regressions altering the inclusion of different control variables (results not reported).

[37] For more analyses on the suitability of the definition of the treatment and control groups, see Lehnert et al. (2020) and Pfister et al. (2021).

treatment group. Furthermore the results are not an artifact of an endogeneous location of the newly established UASs to up-and-coming regions.

7 Conclusion

In this paper, we investigate how the innovation effects from newly established UASs—bachelor-granting three-year colleges teaching and conducting applied research—differ across regions. The heterogeneity in innovation effects that we are able to detect are caused by differences in the regional economic preconditions.

The empirical analysis shows first that *labor market size*, *labor market density* and *high tech intensity* strongly determine whether innovation effects from UASs occur and how large they are. The larger or denser a municipality's labor market before the establishment of a UAS, the higher the innovation effects associated with that UAS—with the largest 25% of the municipalities being those who profited most. Moreover, we find that *high tech intensity* fosters innovation effects from UASs, on average, for all municipalities that have an above median *high tech intensity*. Second, studying the evolution of the treatment effect over time shows that in the municipalities in quartile IV with respect to *labor market size* and *labor market density*, the treatment effect becomes positive some 6 years after the establishment of a UAS. Regarding *high tech intensity*, however, only the municipalities in quartile III show a positive time trend. Third, a joint analysis of all three economic preconditions reveals that *labor market size* is clearly the most important factor fostering innovation effects from UASs and is, thus, also the crucial driver behind the heterogeneity in innovation effects. The same patterns hold, when we focus on patent quality, instead of patent quantity. Our findings are furthermore robust to alternative definitions of the economic preconditions, to the inclusion of a number of other regional characteristics and are not driven by the patent activities in a particular treatment group or by endogeneity in the location of newly established UASs.

We, therefore, argue that the innovation effects due to the establishment of UASs depend on the economic preconditions of a municipality, through agglomeration economies, i.e., benefits that arise from the grouping of individuals or firms in regions or industrial clusters (Glaeser 2010). Our findings contribute to the theoretical discussion in two ways: First, we analyze the heterogeneity in innovation effects of higher education institutions linked to differences in the regional economy. We do so, because the theoretical literature on agglomeration economies mentions three explanations for agglomeration economies that depend on the size and structure of the economic preconditions and potentially increase innovation effects of higher education institutions: they are matching, learning and sharing (Duranton and Puga 2004).

We mirror these three theoretical concepts using our dataset: the concept of matching, i.e., the improvement of the quality and the lowering of costs of labor market matches when more (high-skilled) individuals are involved, is represented by *labor market size* (the more workers and jobs are around, the better are the labor market matches); the concept of learning, i.e., the idea that a high density of individuals in a region facilitates knowledge spillovers, is represented by *labor market density* (the geographically closer workers are, the larger are the knowledge spillovers); and the concept of sharing of infrastructure, i.e., the existence of economies of scales through the clustering of innovative inputs (e.g. laboratories, specialized input goods or particular knowledge) when industries are clustered, is represented by *high tech intensity* (the more high tech companies in close proximity, the more sharing of innovative infrastructure and of knowledge may occur).

Our findings thereby contribute to the empirical testing of the theoretical prediction that these agglomeration economies lead to heterogeneity in innovation effects of higher education institutions. We show empirically that this prediction holds in the case of higher education institutions that teach and conduct *applied* research.[38]. Thus, *labor market size*, *labor market density* and *high tech intensity* have the potential to facilitate innovation effects of higher education institutions teaching and conducting applied research, by providing an economic environment with better and cheaper labor market matches, higher chances of knowledge spillovers and economies of scales in specialized inputs needed for innovation, respectively.

Second, our analysis of the relative importance of different economic preconditions contributes to the theoretical discussion on the relative importance of different mechanisms of agglomeration economies, i.e., matching, sharing or learning. Our finding that *labor market size* is the most important factor points to the fact that the theoretical concept of matching plays the most important role in promoting innovation effects of higher education institutions. The stronger innovation effects in regions with a large labor market give some evidence that agglomeration economies happen mainly through a large enough local labor market that productively absorbs graduates of higher education institutions. The additional supply of qualified workers together with a large enough local labor market guarantees labor market matches that, first, meet the quality standards of graduates, so graduates have a larger incentive to stay in the region. Second, matching costs of firms become lower, thus, firms have an incentive to hire more. As a result, the likelihood of innovations increases due to a higher skilled and a better matched workforce close to newly established UASs.

However, this study also has potential limitations that should be addressed in future research. The limitations arise both due to data availability and methodological challenges. Regarding data availability, we see at least three limitations. First, our study only focuses on outcomes for patent quantity and patent quality while it remains unclear whether the UASs also affect other regional economic outcomes such as the number of firms or employees as well as regional labor market productivity or GDP. Second, for the analyses of patent data, but even more so for broader economic or social outcomes, including UASs teaching other than STEM fields would be an important direction for future research.[39] Third, the current data on UASs contains no information on the size of UASs (e.g, students, professors, budget) nor on their development over time. Thus, the treatment is only binary, a UAS exists or not. Therefore, this study is not able to identify additional sources of potential heterogeneity or economies of scale in innovation effects. Future research should address these questions.

[38] Other empirical studies already analyzed these predictions in the case of higher education institutions that teach and conduct *basic* research (e.g., Varga 2000).

[39] Apart from STEM, i.e., Engineering, IT, chemistry and the life sciences, UASs also teach (1) agriculture and forestry; (2) architecture, construction and planing; (3) music, theater and other arts; (4) design; (5) health; (6) applied linguistics; (7) business, management and services; (8) applied psychology; (9) social work and (10) sports.

Regarding methodology, we see one important limitation. A similar analysis of innovation effects of academic universities would, first, contribute to the discussion whether innovation effects are stronger for basic or applied research, respectively. Second, analyzing potential complementary effects between academic universities and UASs would be of great importance to investigate the joint effects of basic and applied research and disentangle the mechanisms. However, we are not able to identify the innovation effects of academic universities because there are too few new establishments in the relevant time period, leaving us with too little variation across regions and time.[40]

From a policy perspective, our results yield important implications. Not all regions will profit equally from a nearby higher education institution that teaches and conducts applied research, at least not in terms of innovation effects. However, even if innovation effects might not be the primary policy goal of higher education institutions, our findings illustrate an important trade-off between efficiency and equity. Policymakers deciding where new higher education institutions of applied research should be located, need to consider the economic preconditions of the respective regions. On the one hand, when establishing higher education institutions of applied research with the objective of generating the strongest possible innovation effect, the new institutions should be located in local economies with a larger or a denser labor market or an above median *high tech intensity*. The use of educational expansions as a means of developing regional economies—as, for example, postulated by economists to compensate regions for increased import competition due to globalization[41]—might, therefore, be harmful for public spending efficiency goals if they do not fall on fertile ground. On the other hand, if the objective of establishing higher education institutions of applied research is to improve equity, establishing them in remote areas might be reasonable. Or, as Glaeser and Hausman (2020) suggest: An educational expansion can lead to spatial reallocation in public funds and, thus, regionally foster innovation. However, if this reallocation of funds does not maximize aggregate knowledge production, this comes at either the cost of a lower aggregate increase in innovation or at higher public spending to ensure the same increase in innovation activities.

Appendix 1: Policy reform

See Table 4.

[40] Ten out of 12 academic universities were established before 1970.

[41] For an article on the discussion in the US, see Atkinson et al. (2019). For an article on the German discussion, see NZZ (2018).

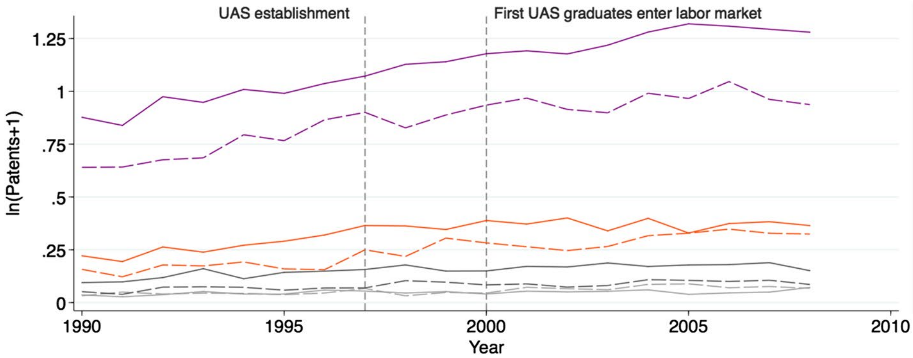
Table 4 Location and year of establishment of all UAS campuses in STEM

UAS	Location of campuses	Year of establishment
Bern UAS	Biel	1997
	Burgdorf	1997
	Bern	1997–2003
UAS of Eastern Switzerland	Chur	2000
	St.Gallen	2000
	Buchs	2001
	Rapperswil	2001
UAS of Zurich	Winterthur	1998
	Wädenswil	1998
	Zürich	1998
UAS of Central Switzerland	Horw	1997
UAS of Northwestern Switzerland	Muttenz	1997
	Brugg-Windisch	1998
	Oensingen	1998–2003
	Olten	2003–2006
UAS of Western Switzerland	Fribourg	1997
	Geneva	2002
	Sion	1998
	Yverdon-les-Bains	1998
	Le Locle	1998–2011
	Saint-Imier	1998–2011
	Neuchâtel	2011
UAS of Southern Switzerland	Manno	1997

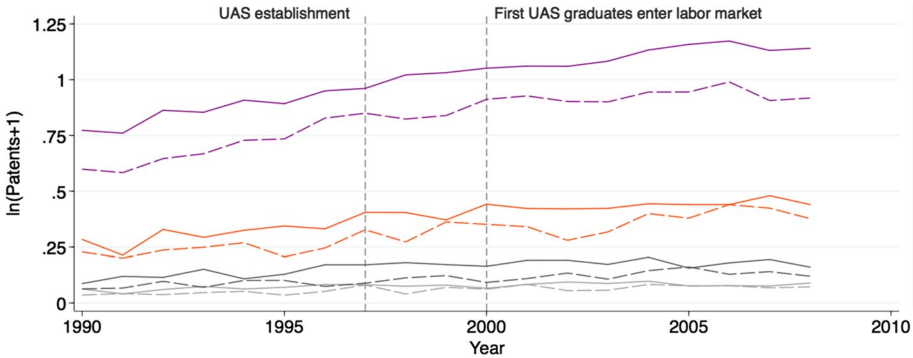
The table shows for all seven UAS umbrella organizations and all 22 campuses the year of establishment. The UAS in Neuchatel is not included in our analysis, because it was established after 2008, nevertheless it is listed here for completeness

Appendix 2: Parallel trends and treatment variation

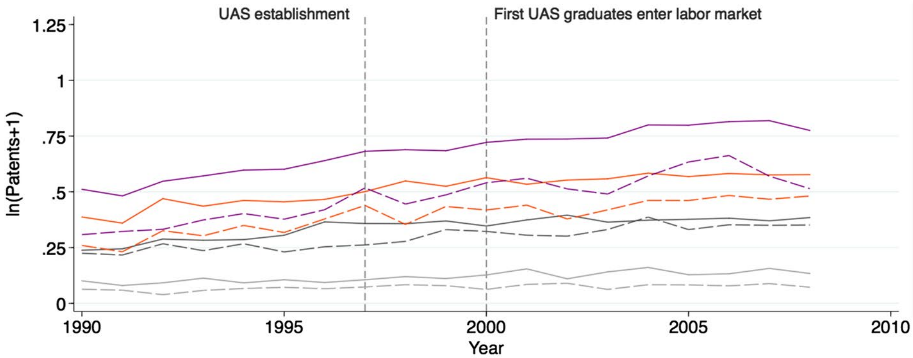
See Figs. 6, 7 and Table 5.



(a) *labor market size*



(b) *labor market intensity*



(c) *high tech intensity*

◀ **Fig. 6** Parallel trends for municipalities by economic preconditions. *Notes* The figure shows the evolution of the ln(patent priority filings + 1) over time for *labor market size* in panel **a**, *labor market density* in panel **b** and *high tech intensity* in panel **c**. Each panel depicts the time trend for ln(patent priority filings + 1) in quartiles I through IV and divided into treatment and control groups. The parallel trends of ln(patent priority filings + 1) for treatment and control groups with respect to each quartile and economic precondition gives some support for the parallel trends assumption to hold. The two vertical lines indicate (1) the point in time when the UASs are established and (2) the period when the first UAS graduates enter the labor market, corresponding to a 3-year lag we assume in the DID.

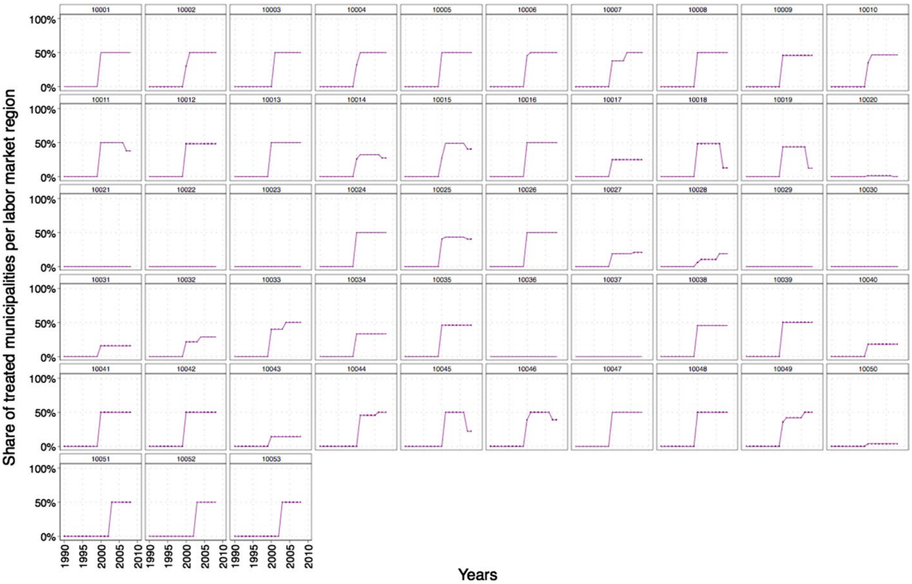


Fig. 7 Variation over time in share of municipalities belonging to treatment or control groups by labor market regions. *Notes* The figure shows for each of the 106 labor market regions the share of treated municipalities over time. There are 22 labor market regions without any treated municipality, 38 labor market regions with all municipalities treated and 46 labor market regions with both treated and nontreated municipalities.

(b)

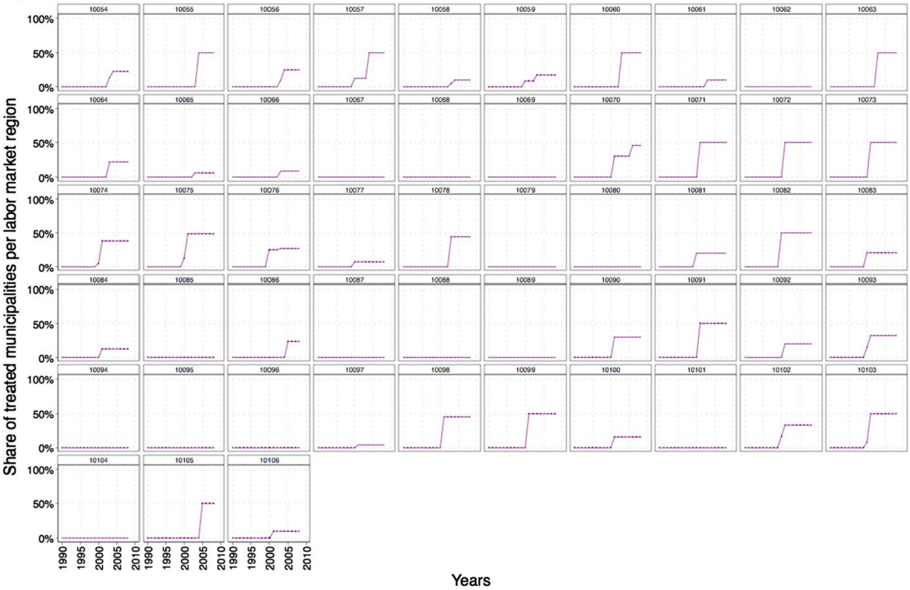


Fig. 7 (continued)

Table 5 Parallel trends: regression results

Dependent variable: ln(patent priority filings+1)	Labor market size (1)	Labor market density (2)	High tech intensity (3)
Treatment group	−0.0670**	−0.0360	−0.0379
	(0.0325)	(0.0340)	(0.0453)
Treatment group x quartile II	−0.0182	−0.0078	−0.0736
	(0.0331)	(0.0333)	(0.0622)
Treatment group x quartile III	0.0195	−0.0369	0.0434
	(0.0422)	(0.0558)	(0.0560)
Treatment group x quartile IV	0.1306	0.1071	0.1083
	(0.0888)	(0.0949)	(0.0699)
Treatment group x 1991	−0.0260	−0.0285**	−0.0165
	(0.0166)	(0.0131)	(0.0203)
Treatment group x 1992	−0.0072	−0.0040	0.0154
	(0.0183)	(0.0153)	(0.0195)
Treatment group x 1993	0.0034	0.0006	0.0172
	(0.0164)	(0.0193)	(0.0251)
Treatment group x 1994	−0.0067	−0.0162	−0.0125
	(0.0199)	(0.0225)	(0.0250)
Treatment group x 1995	−0.0007	0.0083	−0.0034
	(0.0188)	(0.0193)	(0.0251)
Treatment group x 1996	0.0100	0.0036	−0.0097
	(0.0234)	(0.0248)	(0.0271)
Treatment group x 1997	−0.0160	−0.0259	−0.0054
	(0.0286)	(0.0235)	(0.0308)
Treatment group x 1998	0.0093	0.0081	−0.0013
	(0.0217)	(0.0223)	(0.0271)
Treatment group x 1999	0.0001	−0.0171	−0.0058
	(0.0226)	(0.0248)	(0.0317)
Treatment group x quartile II x 1991	0.0418*	0.0569**	0.0305
	(0.0245)	(0.0258)	(0.0308)
Treatment group x quartile II x 1992	0.0092	−0.0023	−0.0080
	(0.0328)	(0.0304)	(0.0375)
Treatment group x quartile II x 1993	0 .0393	0.0565	0.0156
	(0.0333)	(0.0375)	(0.0428)
Treatment group x quartile II x 1994	0.0041	−0.0002	0.0173
	(0.0355)	(0.0394)	(0.0450)
Treatment group x quartile II x 1995	0.0420	−0.0044	0.0646
	(0.0354)	(0.0409)	(0.0396)
Treatment group x quartile II x 1996	0.0267	0.0695*	0.1074**
	(0.0466)	(0.0384)	(0.0461)
Treatment group x quartile II x 1997	0.0600	0.0840**	0.0881*
	(0.0414)	(0.0356)	(0.0457)
Treatment group x quartile II x 1998	0.0222	0.0361	0.0669
	(0.0420)	(0.0404)	(0.0513)
Treatment group x quartile II x 1999	0.0092	0.0424	0.0310
	(0.0410)	(0.0427)	(0.0467)
Treatment group x quartile III x 1991	0.0338	−0.0139	0.0172
	(0.0309)	(0.0328)	(0.0403)
Treatment group x quartile III x 1992	0.0280	0.0406	0.0006
	(0.0442)	(0.0418)	(0.0462)
Treatment group x quartile III x 1993	−0.0026	−0.0118	−0.0120
	(0.0479)	(0.0518)	(0.0549)
Treatment group x quartile III x 1994	0.0216	0.0163	−0.0030
	(0.0495)	(0.0504)	(0.0498)

Table 5 (continued)

Dependent variable: ln(patent priority filings+1)	Labor market size (1)	Labor market density (2)	High tech intensity (3)
Treatment group x quartile III x 1995	0.0676	0.0739*	0.0132
	(0.0463)	(0.0444)	(0.0441)
Treatment group x quartile III x 1996	0.0897*	0.0269	−0.0300
	(0.0490)	(0.0612)	(0.0545)
Treatment group x quartile III x 1997	0.0670	0.0487	−0.0603
	(0.0583)	(0.0648)	(0.0497)
Treatment group x quartile III x 1998	0.0707	0.0680	0.0686
	(0.0507)	(0.0602)	(0.0517)
Treatment group x quartile III x 1999	−0.0237	−0.0294	−0.0313
	(0.0510)	(0.0630)	(0.0540)
Treatment group x quartile IV x 1991	−0.0139	0.0312	−0.0276
	(0.0578)	(0.0615)	(0.0602)
Treatment group x quartile IV x 1992	0.0684	0.0462	−0.0032
	(0.0536)	(0.0577)	(0.0479)
Treatment group x quartile IV x 1993	0.0220	0.0110	−0.0229
	(0.0594)	(0.0636)	(0.0612)
Treatment group x quartile IV x 1994	−0.0157	0.0217	0.0040
	(0.0667)	(0.0665)	(0.0676)
Treatment group x quartile IV x 1995	−0.0128	−0.0245	0.0242
	(0.0578)	(0.0637)	(0.0596)
Treatment group x quartile IV x 1996	−0.0754	−0.0557	0.0265
	(0.0746)	(0.0781)	(0.0652)
Treatment group x quartile IV x 1997	−0.0494	−0.0371	−0.0339
	(0.0686)	(0.0710)	(0.0658)
Treatment group x quartile IV x 1998	0.0541	0.0157	0.0415
	(0.0738)	(0.0769)	(0.0592)
Treatment group x quartile IV x 1999	0.0148	0.0351	0.0004
	(0.0745)	(0.0775)	(0.0691)
Quartiles	Yes	Yes	Yes
Quartiles x year	Yes	Yes	Yes
Year	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes
Observations	22,220	22,220	22,220
Adj. R^2	0.368	0.337	0.248

Appendix 3: Results main analysis

Table 6 shows the results for *labor market size* in column (1), for *labor market density* in column (2) and for *high tech intensity* in column (3). The effect of interest corresponds to the point estimates of the treatment dummy and the interaction of the treatment dummy and the quartile a municipality belongs to according to the preconditions at hand.

Table 7 shows the most important estimation results from the DiD, including all economic preconditions at the same time. The regression results already provide a first indication that *labor market size* is the most important economic precondition to enhance the positive innovation effect of a nearby UAS (Table 8).

Table 6 Main analysis: results for patent priority filings on labor market size, high-tech intensity and labor market density

Dependent variable: ln(patent priority filings + 1)	Labor market size (1)	Labor market density (2)	High tech intensity (3)
Treatment dummy	− 0.0603***	− 0.0582***	− 0.0306
	(0.0151)	(0.0160)	(0.0194)
Treatment dummy × quartile II	0.0186	0.0273	0.0139
	(0.0154)	(0.0167)	(0.0255)
Treatment dummy × quartile III	0.0654***	0.0750***	0.0835***
	(0.0187)	(0.0200)	(0.0281)
Treatment dummy × quartile IV	0.2225***	0.1813***	0.1304***
	(0.0355)	(0.0345)	(0.0312)
Treatment group	− 0.0620*	− 0.0294	− 0.0322
	(0.0313)	(0.0295)	(0.0413)
Treatment group × quartile II	0.0100	0.0182	− 0.0443
	(0.0233)	(0.0247)	(0.0623)
Treatment group × quartile III	0.0253	− 0.0395	0.0066
	(0.0343)	(0.0433)	(0.0518)
Treatment group × quartile IV	0.0786	0.0533	0.0629
	(0.0958)	(0.0961)	(0.0670)
Quartile II	0.0345**	0.0257	0.1287***
	(0.0153)	(0.0161)	(0.0482)
Quartile III	0.1541***	0.1836***	0.1853***
	(0.0266)	(0.0318)	(0.0399)
Quartile IV	0.7047***	0.6155***	0.2816***
	(0.0830)	(0.0789)	(0.0500)
Year dummies	Yes	Yes	Yes
Labor market FE	Yes	Yes	Yes
Observations	42,218	42,218	42,218
Adj. R^2	0.390	0.352	0.263

The coefficients are obtained by an OLS regression including the economic preconditions *labor market size* in column (1) *labor market density* in column (2) and *high tech intensity* in column (3) as in Eq. (2). Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 7 Main analysis: results for patent priority filings on all three economic preconditions together

Dependent variable: ln(patent priority filings + 1)	3-year lag (1)
Treatment dummy	− 0.0598***
	(0.0174)
Treatment dummy × labor market size QII	0.0097
	(0.0224)
Treatment dummy × labor market size QIII	0.0512*
	(0.0296)
Treatment dummy × labor market size QIV	0.2014***
	(0.0452)
Treatment dummy × labor market density QII	0.0058
	(0.0220)
Treatment dummy × labor market density QIII	− 0.0010
	(0.0297)
Treatment dummy × labor market density QIV	0.0014
	(0.0426)
Treatment dummy × high tech intensity QII	− 0.0239
	(0.0203)
Treatment dummy × high tech intensity QIII	0.0002
	(0.0232)
Treatment dummy × high tech intensity QIV	0.0457*
	(0.0264)
Treatment group dummy	Yes
Quartiles	Yes
Treatment group dummy × quartiles	Yes
Year dummies	Yes
District FE	Yes
Observations	42,218
Adj. R^2	0.401

The coefficients are obtained by OLS regressions including all economic preconditions, as in Eq. (4). Dependent variable: ln(patent priority filings + 1). All interacted variables are also included separately but are omitted for clarity. Fixed effects for regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 8 Main analysis: decomposition of variance of the treatment effect by economic precondition

3-year lag		
	Variance	Share of variance
Labor market size	0.0094	53.36%
2 × Cov(labor market size, high tech intensity)	0.0028	16.01%
2 × Cov(labor market size, labor market density)	0.0026	14.97%
High tech intensity	0.0014	8.02%
2 × Cov(labor market density, high tech intensity)	0.0007	3.86%
Labor market density	0.0007	3.77%
Variance of total treatment effect	0.0176	100%
Observations		11,443

The treatment effects and their variances are obtained by OLS regressions including all economic preconditions, as in Eq. (4). Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets. We calculate the sample variance as follows: Var(Treatment Effect)=Var(size)+ Var(density)+ Var(intensity)+2Cov(size,density)+2Cov(size,intensity) +2Cov(density,intensity)

Appendix 4: Results further analyses

See Tables 9, 10 and 11.

Table 9 Further analysis: patent quality measures on labor market size

Dependent variable:	ln(grant ratio + 1)	ln(citation ratio 3-year lag + 1)	ln(citation ratio 5-year lag + 1)	ln(claims ratio USPTO + 1)	ln(claims ratio EPO + 1)	ln(average patent family size + 1)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment dummy	0.0049	− 0.0257***	− 0.0380***	− 0.0280	− 0.0353	− 0.0382
	(0.0038)	(0.0077)	(0.0120)	(0.0230)	(0.0235)	(0.0237)
Treatment dummy × quartile II	0.0049	0.0151	0.0269*	0.0303	0.0416	0.0463
	(0.0052)	(0.0102)	(0.0138)	(0.0333)	(0.0306)	(0.0292)
Treatment dummy × quartile III	− 0.0001	0.0366***	0.0635***	0.0421	0.0940***	0.0843***
	(0.0058)	(0.0092)	(0.0147)	(0.0322)	(0.0309)	(0.0282)
Treatment dummy × quartile IV	− 0.0218***	0.0834***	0.1369***	0.0287	0.1595***	0.1005***
	(0.0072)	(0.0135)	(0.0193)	(0.0307)	(0.0337)	(0.0294)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,218	42,218	42,218	42,218	42,218	42,218
Adj. R^2	0.231	0.133	0.175	0.209	0.247	0.288

The coefficients are obtained by an OLS regression including the economic precondition *labor market size* as in Eq. (2). The dependent variables are the natural logarithms of the following patent quality measures: (1) granted patents per patent application; (2) citations per patent application, with 3-year lag; (3) citations per patent application, with 5-year lag; (4) number of claims per patent application according to the US patent office; (5) number of claims per patent application according to the European patent office; (6) average family size (i.e., the number of countries a patent is protected in) per patent application. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 10 Further analysis: patent quality measures on labor market density

Dependent variable:	ln(grant ratio + 1)	ln(citation ratio 3-year lag + 1)	ln(citation ratio 5-year lag + 1)	ln(claims ratio USPTO + 1)	ln(claims ratio EPO + 1)	ln(average patent family size + 1)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment dummy	0.0064	− 0.0269***	− 0.0343***	− 0.0076	− 0.0113	− 0.0272
	(0.0046)	(0.0077)	(0.0119)	(0.0232)	(0.0267)	(0.0243)
Treatment dummy × quartile II	0.0009	0.0155	0.0206	− 0.0055	0.0041	0.0213
	(0.0047)	(0.0106)	(0.0155)	(0.0319)	(0.0305)	(0.0265)
Treatment dummy × quartile III	0.0031	0.0480***	0.0758***	0.0495	0.1011***	0.1049***
	(0.0061)	(0.0113)	(0.0151)	(0.0332)	(0.0315)	(0.0272)
Treatment dummy × quartile IV	− 0.0251***	0.0736***	0.1131***	− 0.0212	0.0916**	0.0625**
	(0.0083)	(0.0113)	(0.0179)	(0.0319)	(0.0353)	(0.0280)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,218	42,218	42,218	42,218	42,218	42,218
Adj. R^2	0.196	0.118	0.153	0.185	0.213	0.245

The coefficients are obtained by an OLS regression including the economic precondition *labor market density* as in Eq. (2). The dependent variables are the natural logarithms of the following patent quality measures: (1) granted patents per patent application; (2) citations per patent application, with 3-year lag; (3) citations per patent application, with 5-year lag; (4) number of claims per patent application according to the US patent office; (5) number of claims per patent application according to the European patent office; (6) average family size (i.e., the number of countries a patent is protected in) per patent application. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 11 Further analysis: patent quality measures on high tech intensity

Dependent variable:	ln(grant ratio + 1)	ln(citation ratio 3-year lag + 1)	ln(citation ratio 5-year lag + 1)	ln(claims ratio USPTO + 1)	ln(claims ratio EPO + 1)	ln(average patent family size + 1)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment dummy	0.0117**	− 0.0125	− 0.0190	0.0114	− 0.0084	− 0.0075
	(0.0052)	(0.0108)	(0.0150)	(0.0305)	(0.0263)	(0.0278)
Treatment dummy × quartile II	− 0.0085	0.0127	0.0245	− 0.0197	0.0256	0.0182
	(0.0056)	(0.0118)	(0.0176)	(0.0349)	(0.0296)	(0.0315)
Treatment dummy × quartile III	− 0.0142**	0.0390***	0.0725***	0.0121	0.0982***	0.0577*
	(0.0064)	(0.0136)	(0.0189)	(0.0347)	(0.0351)	(0.0315)
Treatment dummy × quartile IV	− 0.0106	0.0401***	0.0698***	− 0.0052	0.1100***	0.0749**
	(0.0074)	(0.0120)	(0.0174)	(0.0409)	(0.0367)	(0.0328)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,218	42,218	42,218	42,218	42,218	42,218
Adj. R^2	0.147	0.093	0.119	0.144	0.157	0.186

The coefficients are obtained by an OLS regression including the economic precondition *high tech intensity* as in Eq. (2). The dependent variables are the natural logarithms of the following patent quality measures: (1) granted patents per patent application; (2) citations per patent application, with 3-year lag; (3) citations per patent application, with 5-year lag; (4) number of claims per patent application according to the US patent office; (5) number of claims per patent application according to the European patent office; (6) average family size (i.e., the number of countries a patent is protected in) per patent application. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Appendix 5: Results robustness tests

See Tables 12, 13, 14, 15 and Figs. 8, 9, 10, 11, 12.

Table 12 Municipalities' assignment to quartiles by employment and firm based economic preconditions

		Quartile I	Quartile II	Quartile III	Quartile IV	
Number of firms (size)						
Labor market size	Quartile I	483	73	0	0	556
	Quartile II	68	402	85	0	555
	Quartile III	8	77	407	64	556
	Quartile IV	1	1	62	491	555
	Total	560	553	554	555	2,222
Firm density						
Labor market density	Quartile I	392	142	21	1	556
	Quartile II	132	272	143	8	555
	Quartile III	28	112	282	134	556
	Quartile IV	4	29	112	410	555
	Total	556	555	558	553	2,222
High tech firm intensity						
High tech intensity	Quartile I	486	63	6	1	556
	Quartile II	56	297	153	49	555
	Quartile III	11	136	232	177	556
	Quartile IV	3	59	165	328	555
	Total	556	555	556	555	2,222

The table reflects the number of municipalities in each of the four quartiles, when split into quartiles according to either employment-based or firm-based economic preconditions

Table 13 Robustness test: results for patent priority filings on labor market size, including control variables

Dependent variable:	Labor market size						
ln(patent priority filings + 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment dummy	− 0.0614***	− 0.0599***	− 0.0614***	− 0.0612***	− 0.0638***	− 0.0615***	− 0.0606***
	(0.0151)	(0.0143)	(0.0143)	(0.0143)	(0.0145)	(0.0145)	(0.0145)
Treatment dummy × quartile II	0.0180	0.0171	0.0163	0.0159	0.0178	0.0160	0.0161
	(0.0149)	(0.0152)	(0.0151)	(0.0151)	(0.0152)	(0.0149)	(0.0151)
Treatment dummy × quartile III	0.0695***	0.0698***	0.0699***	0.0699***	0.0717***	0.0711***	0.0693***
	(0.0191)	(0.0193)	(0.0192)	(0.0193)	(0.0193)	(0.0189)	(0.0188)
Treatment dummy × quartile IV	0.2163***	0.2132***	0.2154***	0.2152***	0.2185***	0.2153***	0.2130***
	(0.0355)	(0.0364)	(0.0355)	(0.0357)	(0.0354)	(0.0348)	(0.0348)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Upper secondary and tertiary education (in %)	No	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment and economic activity rate (in %)	No	No	Yes	Yes	Yes	Yes	Yes
Foreigners (in %)	No	No	No	Yes	Yes	Yes	Yes
Age groups 20–64 and 64+ (in %)	No	No	No	No	Yes	Yes	Yes
Commuter per 100 inhabitants	No	No	No	No	No	Yes	Yes
Typology of the municipality (9 classes)	No	No	No	No	No	No	Yes
Observations	40,356	40,356	40,356	40,356	40,356	40,356	40,356
Adj. R^2	0.394	0.403	0.409	0.410	0.414	0.430	0.488

The coefficients are obtained by an OLS regression including the economic precondition *labor market size* as in Eq. (2). Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets and year fixed effects are included. In column (1) we report the estimate without further control variables, since the regression is based on a smaller sample, due to missing data. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 14 Robustness test: results for patent priority filings on labor market density, including control variables

Dependent variable:	Labor market density						
ln(patent priority filings + 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment dummy	− 0.0616***	− 0.0575***	− 0.0603***	− 0.0599***	− 0.0630***	− 0.0629***	− 0.0608***
	(0.0157)	(0.0156)	(0.0156)	(0.0156)	(0.0157)	(0.0157)	(0.0155)
Treatment dummy × quartile II	0.0284*	0.0266	0.0275*	0.0277	0.0301*	0.0336**	0.0308*
	(0.0161)	(0.0166)	(0.0165)	(0.0167)	(0.0168)	(0.0162)	(0.0162)
Treatment dummy × quartile III	0.0786***	0.0739***	0.0750***	0.0743***	0.0767***	0.0789***	0.0773***
	(0.0198)	(0.0206)	(0.0204)	(0.0206)	(0.0203)	(0.0204)	(0.0195)
Treatment dummy × quartile IV	0.1805***	0.1756***	0.1798***	0.1797***	0.1840***	0.1840***	0.1834***
	(0.0340)	(0.0354)	(0.0338)	(0.0343)	(0.0338)	(0.0326)	(0.0323)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Upper secondary and tertiary education (in %)	No	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment and Economic Activity Rate (in %)	No	No	Yes	Yes	Yes	Yes	Yes
Foreigners (in %)	No	No	No	Yes	Yes	Yes	Yes
Age Groups 20-64 and 64+ (in %)	No	No	No	No	Yes	Yes	Yes
Commuter per 100 inhabitants	No	No	No	No	No	Yes	Yes
Typology of the municipality (9 classes)	No	No	No	No	No	No	Yes
Observations	40,356	40,356	40,356	40,356	40,356	40,356	40,356
Adj. R^2	0.356	0.368	0.378	0.380	0.385	0.406	0.471

The coefficients are obtained by an OLS regression including the economic precondition *labor market density* as in Eq. (2). Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets and year fixed effects are included. In column (1) we report the estimate without further control variables, since the regression is based on a smaller sample, due to missing data. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

Table 15 Robustness test: results for patent priority filings on high tech intensity, including control variables

Dependent variable:	High tech intensity						
ln(patent priority filings + 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment dummy	− 0.0278	− 0.0288	− 0.0313*	− 0.0340*	− 0.0367**	− 0.0323*	− 0.0307*
	(0.0197)	(0.0189)	(0.0184)	(0.0182)	(0.0181)	(0.0186)	(0.0180)
Treatment dummy × quartile II	0.0077	0.0099	0.0061	0.0087	0.0106	0.0043	0.0071
	(0.0263)	(0.0248)	(0.0241)	(0.0235)	(0.0231)	(0.0231)	(0.0227)
Treatment dummy × quartile III	0.0812***	0.0820***	0.0796***	0.0806***	0.0816***	0.0724***	0.0658**
	(0.0279)	(0.0262)	(0.0252)	(0.0250)	(0.0250)	(0.0251)	(0.0256)
Treatment dummy × quartile IV	0.1220***	0.1238***	0.1217***	0.1238***	0.1255***	0.1168***	0.1135***
	(0.0310)	(0.0297)	(0.0287)	(0.0281)	(0.0281)	(0.0270)	(0.0266)
Treatment group	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quartile	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment group × quartiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional labor market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Upper secondary and tertiary education (in %)	No	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment and Economic Activity Rate (in %)	No	No	Yes	Yes	Yes	Yes	Yes
Foreigners (in %)	No	No	No	Yes	Yes	Yes	Yes
Age Groups 20-64 and 64+ (in %)	No	No	No	No	Yes	Yes	Yes
Commuter per 100 inhabitants	No	No	No	No	No	Yes	Yes
Typology of the municipality (9 classes)	No	No	No	No	No	No	Yes
Observations	40,356	40,356	40,356	40,356	40,356	40,356	40,356
Adj. R^2	0.264	0.303	0.335	0.349	0.358	0.400	0.473

The coefficients are obtained by an OLS regression including the economic precondition *high tech intensity* as in Eq. (2). Dependent variable: ln(patent priority filings + 1). Fixed effects for regional labor markets and year fixed effects are included. In column (1) we report the estimate without further control variables, since the regression is based on a smaller sample, due to missing data. Robust standard errors are clustered at the level of regional labor markets. The levels of significance are denoted as follows: *** ($p < 0.01$); ** ($p < 0.05$); * ($p < 0.10$)

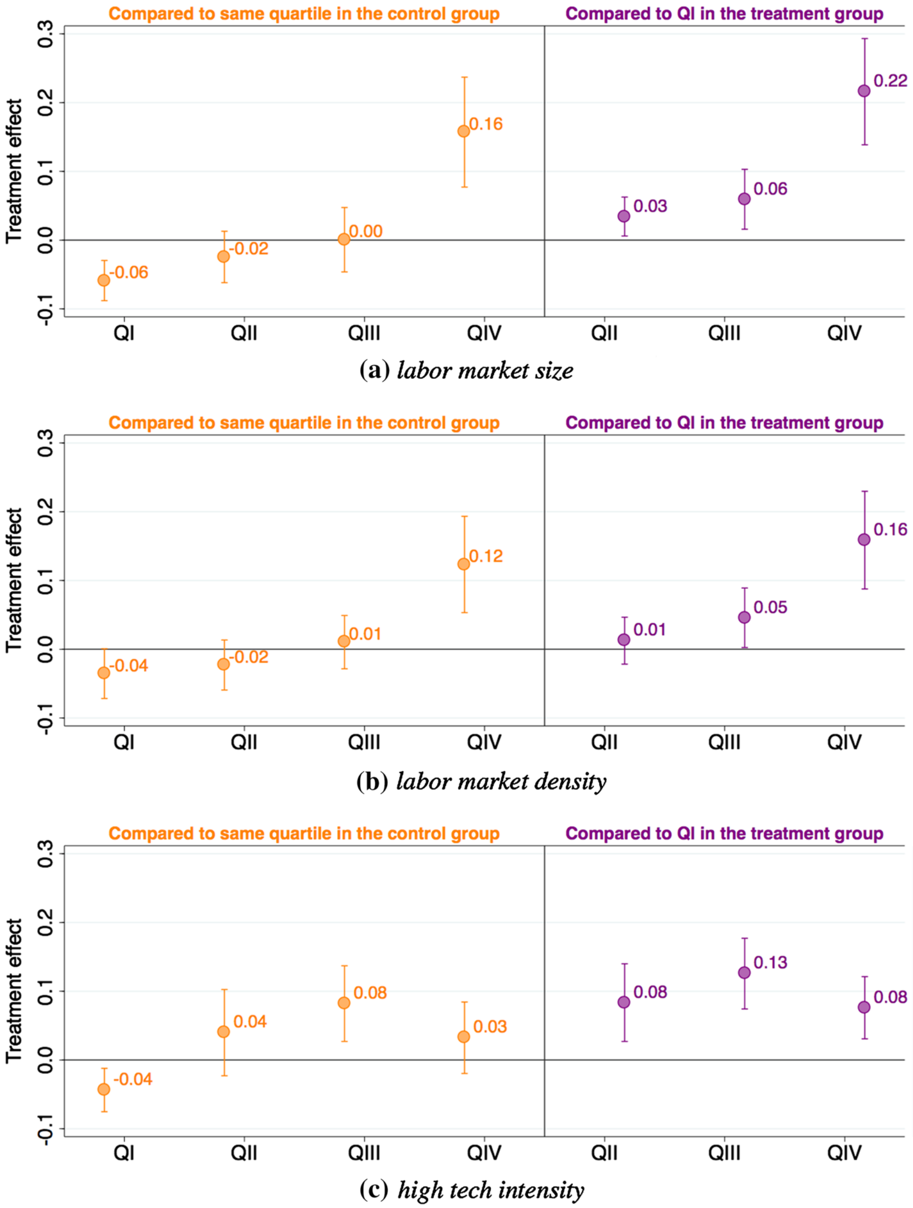


Fig. 8 Treatment effects for municipalities by quartile and economic precondition when defined using firm data instead of employment data. *Notes* The figure shows the coefficients from the OLS regressions for *number of firms (size)* in panel **a**, *firm density* in panel **b** and *high tech firm intensity* in panel **c**. Dependent variable: ln(patent priority filings + 1). Left-hand side of panels: treatment effects in the treated municipalities relative to the nontreated municipalities in the same quartile, i.e., $\gamma + \delta_k$ from Eq. (2). Right-hand side of panels: treatment effect in the treated municipalities relative to the treated municipalities in quartile I, i.e., δ_k from Eq. (2). The fixed effects for the regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets

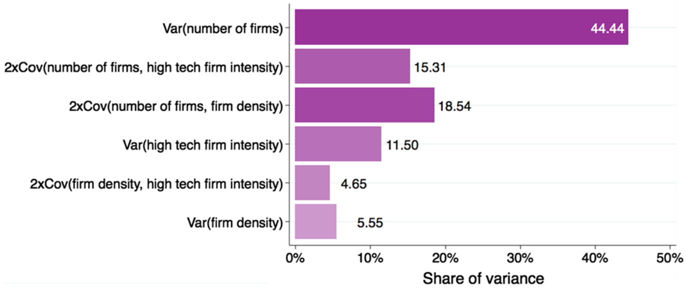


Fig. 9 Variance of the treatment effect explained by economic preconditions when defined using firm data instead of employment data. *Notes* The figure shows the share of the variance in the treatment effect, obtained by an OLS regression including all economic preconditions, as in Eq. (4), explained by different economic preconditions. Dependent variable: ln(patent priority filings + 1). We calculate the sample variance as follows: Var(Treatment Effect)=Var(size)+ Var(density)+Var(intensity)+2Cov(size,density) +2Cov(size,intensity)+2Cov(density,intensity).

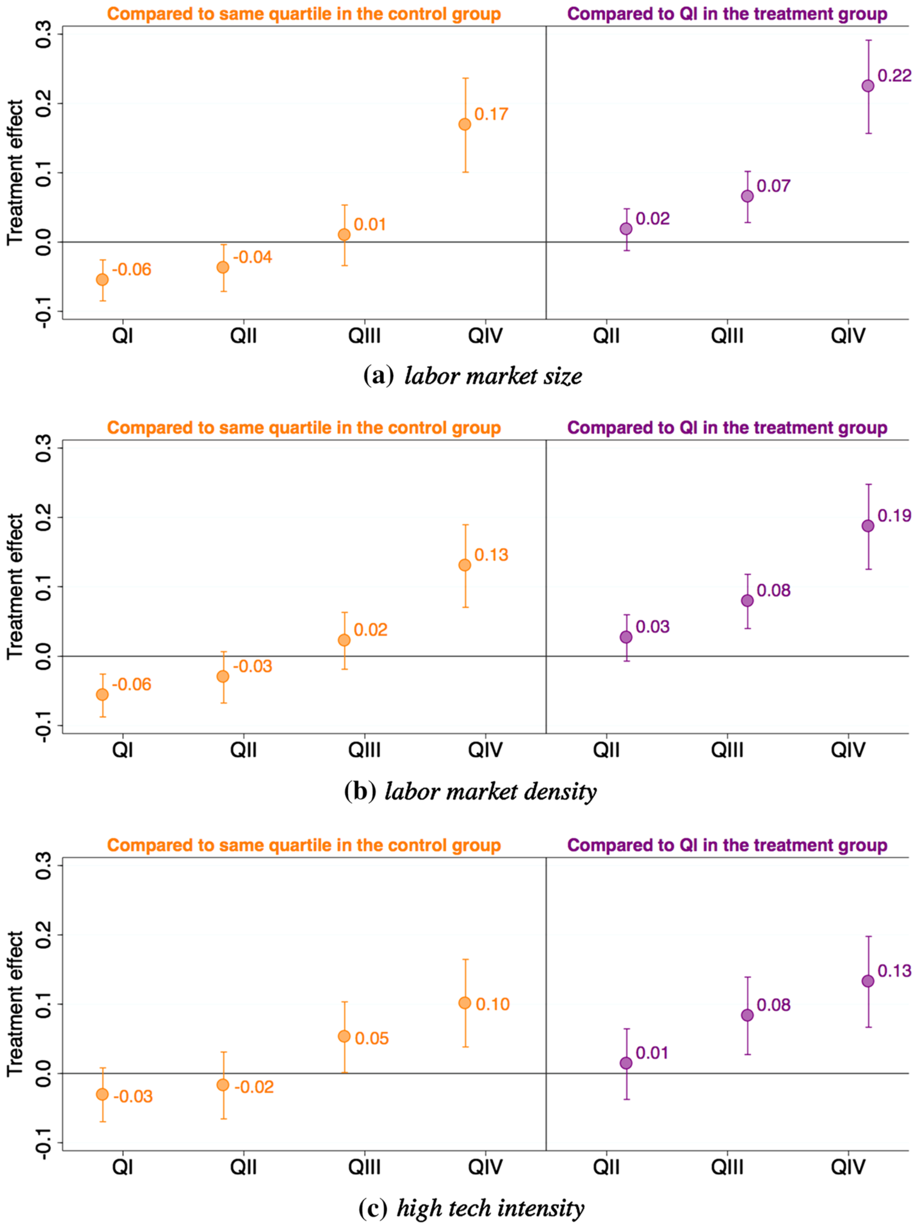


Fig. 10 Treatment effects for municipalities by quartile and economic precondition when excluding municipalities in the top decile. *Notes* The figure shows the coefficients from the OLS regressions, excluding the municipalities in the top decile for *labor market size* in panel **a**, *labor market density* in panel **b** and *high tech intensity* in panel **c**, respectively. Dependent variable: ln(patent priority filings + 1). Left-hand side of panels: treatment effects in the treated municipalities relative to the nontreated municipalities in the same quartile, i.e., $\gamma + \delta_k$ from Eq. (2). Right-hand side of panels: treatment effect in the treated municipalities relative to the treated municipalities in quartile I, i.e., δ_k from Eq. (2). The fixed effects for the regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets.

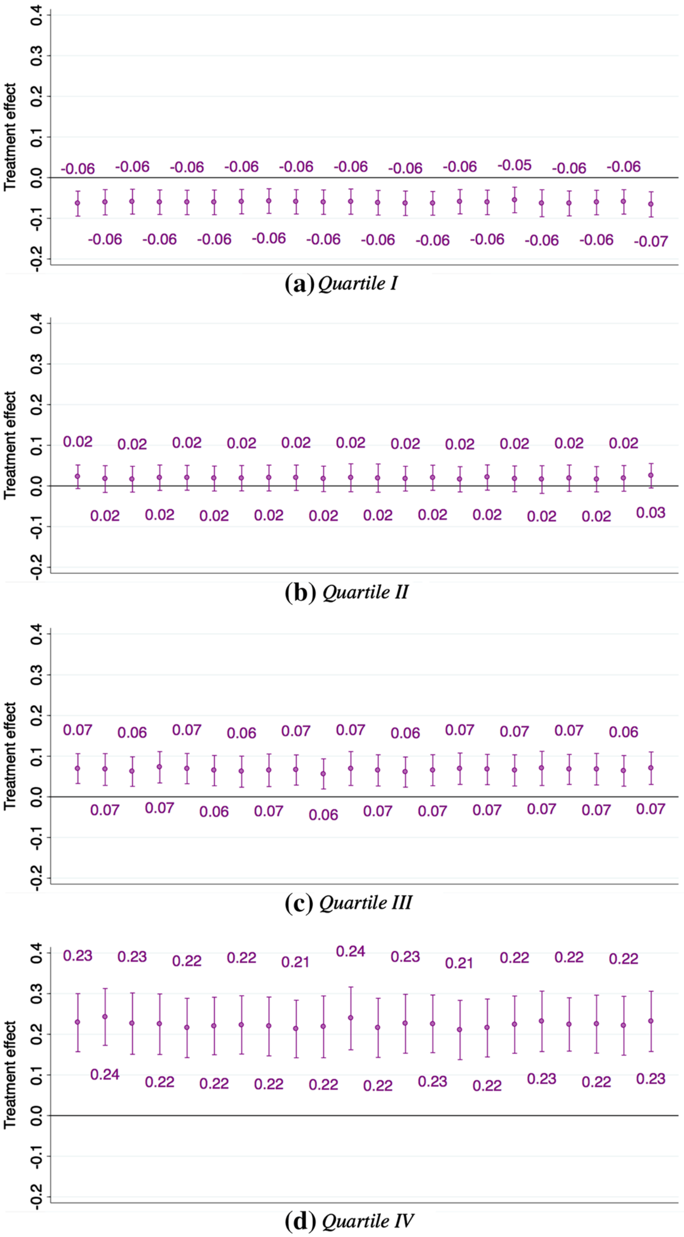


Fig. 11 Treatment effects for municipalities by quartile and economic precondition when one treatment group at a time is dropped. *Notes* The figure shows the coefficients from OLS regressions for *labor market size*, with vertically aligned dots being coefficients from the same regressions. In each regression, one treatment group at a time is omitted. The panels **a** to **d** show the results for the different quartiles. Dependent variable: ln(patent priority filings + 1). The coefficients represent treatment effects in the treated municipalities relative to the nontreated municipalities in the same quartile, i.e., $\gamma + \delta_k$ from Eq. (2). The fixed effects for the regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets.

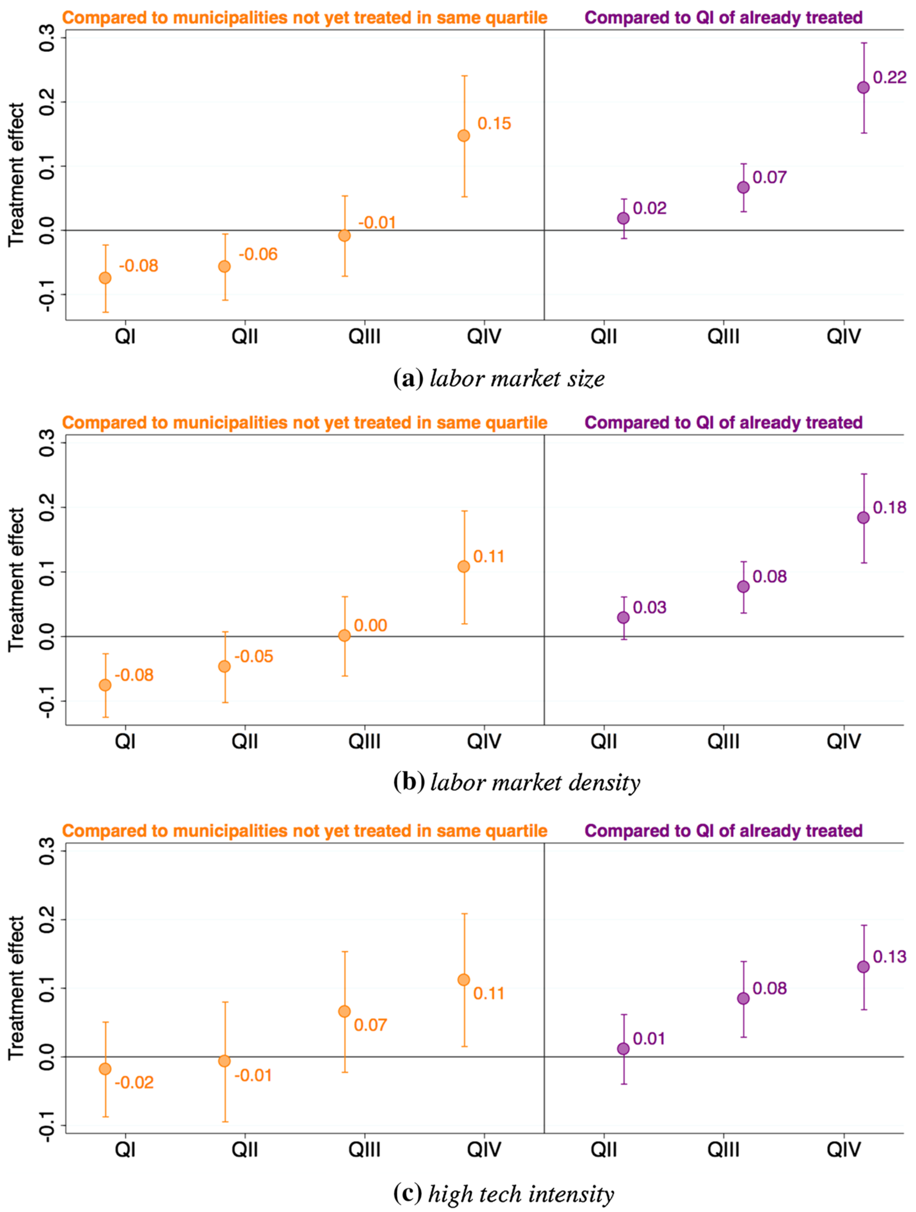


Fig. 12 Treatment effects for municipalities by quartile and economic precondition when using only variation in the UAS establishment over time. *Notes* The figure shows the coefficients from the OLS regressions, where only the variation in the treatment over time is used (control group is dropped) for *labor market size* in panel **a**, *labor market density* in panel **b** and *high tech intensity* in panel **c**, respectively. Dependent variable: ln(patent priority filings + 1). Left-hand side of panels: treatment effects in the treated municipalities relative to the municipalities not yet treated in the same quartile, i.e., $\gamma + \delta_k$ from Eq. (2). Right-hand side of panels: treatment effect in the treated municipalities relative to the municipalities already treated in quartile I, i.e., δ_k from Eq. (2). The fixed effects for the regional labor markets and year fixed effects are included. Robust standard errors are clustered at the level of regional labor markets.

Acknowledgements This paper has benefited from many audiences and exchanges. In particular we would like to thank the anonymous referee for the helpful comments as well as the following individuals for their help and support: Simone Balestra, Eric Bettinger, Thomas Dohmen, Simon Janssen, Edward Lazear, Jens Mohrenweiser, Samuel Muehlemann, Natalie Reid, Paul Ryan, Guido Schwerdt and the seminar participants at the University of Zurich. We furthermore thank Pascal Meier for data collection and the Swiss Federal Statistical Office (SFSO) for the data provision. This study is partly funded by the Swiss State Secretariat for Education, Research, and Innovation (SERI) through its Leading House on the Economics of Education, Firm Behavior and Training Policies.

Funding Open Access funding provided by Universität Zürich. This study is partly funded by the Swiss State Secretariat for Education, Research, and Innovation (SERI) through its Leading House on the Economics of Education, Firm Behavior and Training Policies.

Availability of data and material Data on the UAS establishment is provided in Table 4 in Appendix 1. Business census data is not publicly available and was provided by the Swiss Federal Statistical Office (statent@bfs.admin.ch). Patent data is not publicly available and was provided by the European Patenting Office.

Code availability Stata code can be made publicly available, otherwise not applicable.

Compliance with ethical standards

Conflict of interest Not applicable.

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