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The Role of Fields of Study for the Effects of Higher Education Institutions on Regional Firm Location

Tobias Schlegel[a,*], Uschi Backes-Gellner[a]

Abstract

The literature on knowledge spillovers provides evidence that higher education institutions (HEIs) positively affect regional firm location (i.e., start-ups or firms located in a region). However, less is known about how HEIs in different fields of study impact regional firm location in different industries. To investigate this question, we exploit the establishment of universities of applied sciences (UASs)——bachelor's degree-granting three-year HEIs in Switzerland. We find that the effects of UASs are heterogeneous across fields of study and industries. UASs specializing in "chemistry and the life sciences" and "business, management, and services" are the only UASs that positively affect regional firm location across several industries. Positive effects emerge in service industries characterized by radical service, incremental product, or process innovations. Thus, UASs are not a one-size-fits-all solution for increasing regional firm location. Instead, only UASs specializing in particular fields of study positively influence firm location in certain industries.

Keywords: Higher Education and Research Institutions, Government Policy, Regional Economic Development

JEL Classification: I23, I28, O18

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1. Introduction

The literature on knowledge spillovers states that the two main knowledge outputs of higher education institutions (HEIs), the creation of new knowledge and of specialized human capital, positively affect the number of start-ups or firms that locate in a region, i.e., regional firm location (e.g., Acs and Sanders 2013; Audretsch and Lehmann 2005a; Kirchhoff et al. 2007). Yet the usefulness of both new knowledge and specialized human capital for firms——and thus the potential impact of HEIs on firm location

——heavily depends on the field(s) of study in which an HEI specializes, and which defines the institution's knowledge output (Audretsch and Lehmann, 2005b; Fritsch and Aamoucke, 2017). Therefore, the field(s) of study that an HEI as the knowledge supplier offers is a first important source of heterogeneity in the effect of HEIs on firm location.

Similar reasoning for heterogeneity applies to the knowledge inputs that firms locating in a region are planning to obtain from HEIs. Their required inputs depend on the absorptive capacity of their firm as well as the type of production, processes, or services of the industry. These firm- and industry-specific characteristics determine how new knowledge and specialized human capital can be absorbed (Bonaccorsi et al., 2013; Qian and Acs, 2013). Thus the industry to which a firm as the knowledge consumer belongs is a second important source of heterogeneity for the effect of HEIs in different fields of study on firm location.

Consequently, the impact of HEIs on firm location depends on the matching of the HEIs' knowledge output—as the knowledge suppliers—and the the local firms' required knowledge inputs—as the knowledge consumers. For a positive impact

of HEIs on firm location, the knowledge output of HEIs in particular fields must match the knowledge inputs that firms in particular industries need in an efficient manner (Barra et al., 2021; Landry et al., 2007).

As knowledge spillovers tend to be geographically localized (Anselin et al., 1997; Boschma, 2005), a productive matching of knowledge outputs of HEIs with knowledge inputs of firms, requires the regional co-location of the corresponding HEIs and firms (Barra et al., 2021; Landry et al., 2007). However, policies targeted at promoting regional firm location, e.g., by establishing HEIs in a region, often neglect this need for a regional match of HEI knowledge outputs and of knowledge inputs that firms in particular industries need (Prokop and Stejskal, 2018). One reason for this neglect is that empirical evidence is missing on how HEIs specializing in different fields of study affect regional firm location across different industries (for an exception, see Bonaccorsi et al. 2013.

Furthermore, two factors linked to heterogeneous effects of HEIs on firm location have been thus far overlooked. On one hand, the HEIs analyzed in earlier studies are mostly academic universities conducting basic research (except for Fritsch and Aamoucke 2017). Although applied knowledge is critical for the emergence of new marketable products and services (Barra et al., 2021; Graf and Menter, 2021; Maietta, 2015), the impact of HEIs producing applied knowledge and specializing in different fields of study on firm location is under-researched, particularly for differences across industries. On the other hand, most earlier studies focus solely on firm location across manufacturing industries. However, given that innovative service industries play a predominant role in advanced economies (Mina et al., 2014), missing research on service industries represents a severe shortage and, thus far, research results remain insufficient for regional policy-making.

Therefore, this study asks and answers the question of how HEIs that teach and conduct applied research and that specialize in different fields of study affect firm location across different manufacturing and service industries. Using Switzerland as a case study, we analyze the impact of the establishment of universities of applied sciences (UASs)—bachelor's degree-granting three-year HEIs—in different fields of study on firm location across different industries. We expect heterogeneous impacts of UASs on regional firm location across industries. Positive effects of UASs on regional firm location are expected to occur especially in industries where the knowledge output produced by a UAS specializing in a field of study matches the knowledge inputs required by firms in this very industry. However, for industries whose knowledge inputs do not match the knowledge outputs of a regional UAS, the impact of UASs on firm location might be absent or even negative, as firms in these industries either perish due to for example a lack of their required human capital or relocate to other regions.

For our analysis, we combine two data sets. First, we self-collected a new data set on the establishment of all UASs in all fields of study in Switzerland, starting in the mid-1990s, to measure regional and temporal variation in the exposure to a UASs specializing in a particular field of study. In so doing, we use data comprising information on all Swiss municipalities, i.e., the smallest political entities, that have a new UAS campus specializing in any field of study. The data on the establishment of UASs allows us to assign municipalities to treatment and control groups. We group the variety of study programs that UASs offer into eight fields of study as defined by the Swiss federal department of Economic Affairs, Education and Research (EAER, 2014).[1]

[1]The fields of study are (1) "Chemistry & Life Sciences"; (2) "Business, Management &

Second, to measure regional and time variation in firm location, we use data from the Swiss business census, a full survey of all firms in the manufacturing and service industries. To represent the different knowledge inputs needed across different industries, we require an industry taxonomy that groups all manufacturing and service industries according to their required knowledge sources, innovation patterns, and human capital needs.[2]

To this end, we follow Bonaccorsi et al. (2013) who provide a taxonomy that groups *all* manufacturing and service industries into eight industry categories according to their required knowledge sources, innovation patterns, and human capital needs. We use this taxonomy, for two reasons. First, as the taxonomy is constructed to represent the different sources which firms use to access knowledge inputs, we can analyze whether and, if so, how UASs impact firm location differently across industries relying on different knowledge sources. Since our data structure exactly represents the taxonomy, we are thus able to investigate heterogeneity in the effects of UASs on regional firm location across the entire set of manufacturing and service industries' different knowledge inputs. Second, implementing this taxonomy, we can add to the literature on heterogeneity in knowledge spillovers from HEIs by using an identical industry taxonomy but analyzing another type of HEI—UASs with their focus on applied research instead of academic universities with a focus on basic research.

Combining these two data sets at the municipality level is particularly appropriate for our analysis for two reasons. First, by matching the datasets at the

Services"; (3) "Architecture, Construction & Planning"; (4) "Design"; (5) "Engineering & IT"; (6) "Music, Theater & other Arts"; (7) "Health"; and (8) "Social Work".

[2]For manufacturing firms, the categories are (i) science-based, (ii) supplier-dominated, (iii) scale-intensive, and (iv) specialized manufacturing; for service firms, the categories are (i) knowledge-intensive, (ii) supplier-dominated, (iii) physical network, and (iv) information network services.

municipality level, i.e., at a fine-grained regional level, we are able to detect the impacts of HEIs on firm location, even though they are expected to be geographically localized (Audretsch and Lehmann, 2005b; Fritsch and Aamoucke, 2013). Second, the fine-grained municipality structure provides us with many observations and large variation in field-industry combinations for our empirical analysis. This large number of field-industry combinations allows us to go beyond earlier studies on the impact of HEIs on firm location that have—inter alia due to data restrictions—a narrower focus on manufacturing industries or particular fields of study, or both.

For each of the resulting field-industry combinations, we estimate the effects of the establishment of UASs specializing in a particular field of study on firm location in a particular industry by a two-way fixed effects model including municipality and year fixed effects. We estimate our model, using a Poisson pseudo-maximum likelihood estimator. To deal with potential endogeneity concerns, we implement a novel approach, suggested by Lehnert et al. (2020a), that controls for time-variant regional economic activity by using daytime satellite imagery data. To further control for time-variant differences in regional economic infrastructure, we use detailed data provided by Wuest Parter based on information from a building insurance company on gross floor space use at the municipality level.

Our analysis reveals the following broad patterns of heterogeneity in the effects of UASs on firm location both across different fields of study and across different industries. UASs specializing in Chemistry & Life Sciences Business, Management & Services or in fields linked to engineering (i.e., Architecture, Construction & Planning, Design, and Engineering & IT) are associated with positive effects on firms in service industries, while they show no, or even slight negative effects on

firm location in manufacturing industries. UASs specializing in the humanities (i.e., Music, Theater & other Arts, Health, and Social Work) have virtually no effects on firm location across industries.

These heterogeneous patterns may be explained as follows. First, if effects of UASs on firm location are positive, they occur in service industries characterized by (a) radical service innovations, and (b) incremental product and process innovations. Second, a further analysis provides evidence that these positive effects of UASs are driven by small firms that are potential start-ups. Thus, the knowledge and human capital outputs provided by UASs are particularly valuable as knowledge inputs for small firms that would—in comparison to large firms—otherwise not be able to generate these required knowledge inputs on their own. Third, by providing human capital that allows graduates to successfully manage their transition from manufacturing to service industry jobs, UASs appear to foster a trend towards a more service-oriented economy.

Our findings indicate that UASs and their focus on applied research likely constitute an important complement to academic universities, because the two types of HEIs affect different industries. The positive effects of UASs on industries characterized by both radical service innovations and incremental product and process innovations thus complement the effects of academic universities found in previous studies (Barra et al., 2021; Bonaccorsi et al., 2013), effects that impact regional firm location in industries characterized by radical product innovations. Combining our findings with those of previous studies indicates on one hand that creating a comprehensive regional innovation ecosystem calls for providing sufficient resources to both academic universities and UASs, as complements, not substitutes. On the other hand, for regions outside of major innovation centers

and characterized by industries requiring knowledge inputs for incremental process and product innovations, establishing UASs might be a better targeted policy for fostering regional firm location than establishing a further academic university.

The study is structured as follows. Section 2 outlines the literature and discusses evidence for sources of heterogeneity in firm location across fields of study and industries. Section 4 introduces the data and discusses the categorizations of fields of study and firm industries. Section 5 presents and discusses the empirical strategy for dealing with endogeneity concerns and estimating heterogeneity in firm location across fields of study and industries. Section 6 presents the results, and Section 7 summarizes and concludes.

2. Sources of Heterogeneity in Firm Location across Fields of Study and Industries

Two types of knowledge outputs from HEI have been shown to positively impact regional firm location (Acosta et al., 2011; Braunerhjelm et al., 2010; Uyarra, 2010). The first output is new knowledge created by HEIs in the form of R&D, patents, papers, contract research, or collaborations. Empirical analyses often measure new knowledge through HEI R&D spending, finding a positive impact on regional firm location (Kirchhoff et al., 2007; Woodward et al., 2006). However, the number of patents (Shane, 2001), research collaborations (Walter et al., 2013), or scientists (Harhoff, 1999; Zucker et al., 1998) also positively influences regional firm location.

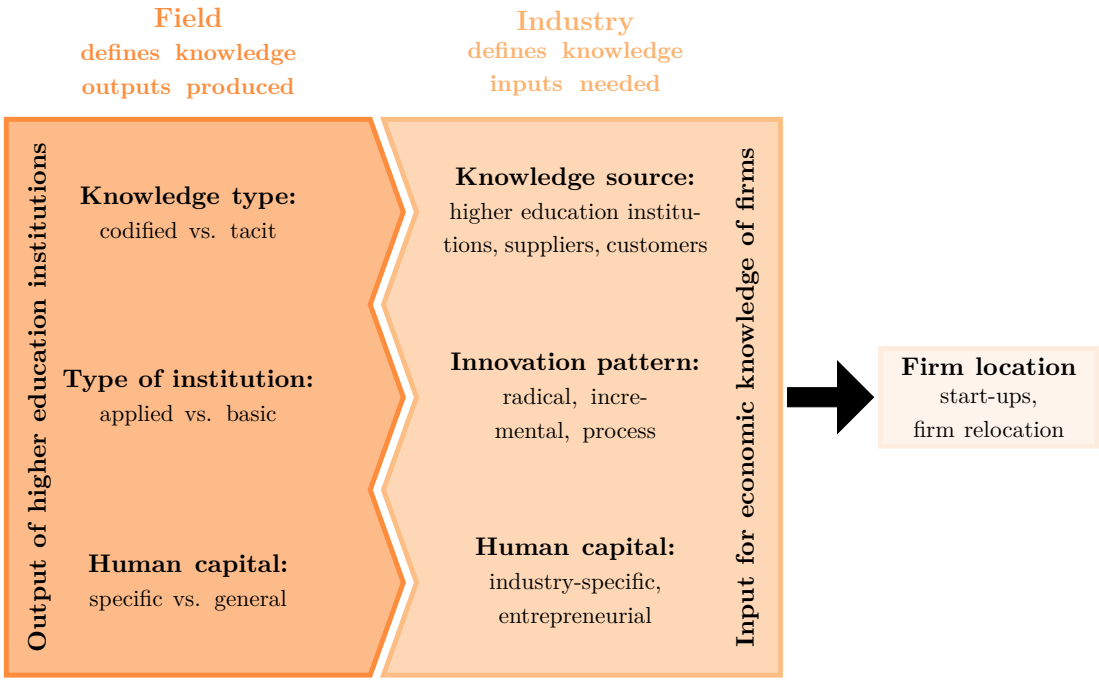
The second output that positively impacts firm location is the human capital of HEI graduates applying their human capital in the regional labor market (Au-

dretsch and Lehmann, 2005b; Varga, 2000; Veugelers and Del Rey, 2014). Comparing the importance of the two HEI outputs for firm location, Acosta et al. (2011) find that graduates are the main source of the positive effects of HEIs on firm location. The importance of human capital for firm location corresponds to the finding that founders of new firms often locate where they had previously studied or worked (Dahl and Sorenson, 2009; Figueiredo et al., 2002; Simha, 2005).

However, evidence exists that both HEI outputs—new knowledge and human capital—differ according to the field(s) of study that the HEI offers (Audretsch and Lehmann, 2005b; Audretsch et al., 2004; Fritsch and Aamoucke, 2017). Thus the literature on knowledge spillovers identifies at least three dimensions along which the HEI outputs differ across fields of study (left-hand side of Fig. 1). Yet the differences implied by these three dimensions have contradictory implications for the impacts of HEI on regional firm location (Baptista and Mendonça, 2010).

First, depending on the field(s) of study that HEIs offer, new knowledge created by these institutions is more or less codified (Acs et al., 2013; Fritsch and Aamoucke, 2013; Kogut and Zander, 1992). Yet the degree to which knowledge is codified influences firm location (Cassia and Colombelli, 2008). On one hand, codified knowledge (e.g., patents, scientific publications or published software codes) can be accessed more or less independently of the location of a firm. Therefore, empirical evidence for positive effects of codified knowledge on firm location is mixed (Hülsbeck and Pickavé, 2014; Piva et al., 2011; Powers and McDougall, 2005)—or as Ghio et al. (2015) put it, codified knowledge is necessary but by far not sufficient for fostering regional firm location.[3]

[3]Furthermore, codified knowledge is also non-excludable and non-rival, meaning that firms can access it without any link whatsoever between them and the HEI (Ghio et al., 2015).



Source: Authors' figure. *Notes*: The left-hand side of Fig. 1 shows potential dimensions across which HEIs knowledge outputs differ across fields of study. These dimensions are reflected by differences in the knowledge needs of industries (middle of Fig. 1) for transferring HEI knowledge into economic knowledge. If the knowledge outputs produced by an HEI specializing in a field of study and the knowledge inputs needed by an industry match, the HEI can positively impact firm location by means of new start-ups or firm relocations (right-hand side of Fig. 1).

Figure 1. Heterogeneity in the knowledge output produced by HEIs across fields of study and the knowledge inputs needed by firms across industries

On the other hand, non-codified, i.e., tacit, knowledge needs the proximity of firms to an HEI because tacit knowledge is embodied in both the HEI and its R&D-conducting employees (Acs and Sanders, 2013; Arundel and Geuna, 2007; Fritsch and Aamoucke, 2013; Maietta, 2015), as well as in the human capital created by the HEIs (Ghio et al., 2015). For differences across fields of study, Audretsch and Lehmann (2005b) state, for example, that knowledge from research in the social sciences is considerably less codified than that in the natural sciences. Indeed, both Audretsch et al. (2005) and Cassia and Colombelli (2008) find that the co-

location of firms with HEIs is more important for exploiting knowledge spillovers from the social sciences than from the natural sciences.[4]

Second, the knowledge produced by different fields of study varies in terms of its potential transferability into economic knowledge. Applied knowledge (e.g., architecture or spatial planning) can be put immediately to commercial use more easily than basic knowledge (e.g., physics and mathematics), which has a less direct practical application (Barra et al., 2021; Bonaccorsi et al., 2013). This immediate application potential of applied knowledge therefore appears to be more favorable for firm location (Maietta, 2015). Fritsch and Aamoucke (2017), and Arundel and Geuna (2007) underpin this argument by showing that research in the applied sciences is more important for firm location than that in the natural sciences. Furthermore, Cohen et al. (2002) argue that basic research impacts a regional economy indirectly, by providing knowledge used by the applied sciences and engineering and only then transferred to the regional economy.

Third, HEI graduates in different fields of study differ in the industry-specificity of the human capital they acquire (Arcidiacono, 2004; Audretsch et al., 2004). The human capital of graduates from the natural sciences and engineering, for example, is more specific than that of graduates in business or the humanities (Kinsler and Pavan, 2015; Lombardo et al., 2012; Silos and Smith, 2015). While graduates in the natural sciences or engineering might have an impact on a small circle of firms that potentially locate in the region, within this highly specialized circle the need for co-location of firms with HEIs in the natural sciences or engineering might be extremely important (Audretsch et al., 2004). In contrast, while the importance for

[4] Broström (2010) argues that the amount of tacit knowledge is bigger at earlier stages of research projects. Thus industries that tend to depend on knowledge inputs from the research frontier might be particularly eager to co-locate with HEIs.

firms to co-locate with HEIs in business or the humanities might be less distinct, co-location of firms with an HEI in these fields might be profitable for a large circle of firms.[5] Either way, the human capital of graduates from HEIs specializing in different fields must match the knowledge inputs that regional industries need for fostering firm location (Maietta, 2015).

As the middle of Fig. 1 shows, the heterogeneity in HEI knowledge outputs across fields of study mirrors the heterogeneity in knowledge inputs that firms in different industries need for producing economic knowledge (Bania et al., 1993). While the fact that the knowledge outputs of HEIs must match the regional knowledge inputs that firms need for knowledge spillovers holds across all industries (Landry et al., 2007), the required knowledge inputs differ across industries.

First, the impact of HEIs across industries differs because firms in different industries obtain knowledge inputs from different sources, not only through R&D and human capital from HEIs but also through information obtained from suppliers of equipment or the users of their products and services (Arundel and Geuna, 2007; von Hippel, 1988). While Arundel and Geuna (2007) find that low- and medium-technology industries (e.g., food or utilities) also rely on the research output of HEIs, suppliers and users are a particularly important knowledge source in the service industries (Tether, 2005). Furthermore, Arundel and Geuna (2007) show that the importance of proximity to an HEI decreases as a firm's R&D expenditure rises, i.e., when internal knowledge sources become more important.

Second, innovation patterns differ across industries, ranging from the predominance of radical product or service innovations to incremental product or process

[5] A somewhat different distinction of specificity is analyzed by Hülsbeck and Pickavé (2014), who show that while undergraduate students play a less important role in high-tech firm location, PhD graduates are the more important factor for high-tech firm location.

innovations (Baptista and Mendonça, 2010; Miozzo and Soete, 2001; Pavitt, 1984). Those firms in industries with an innovation pattern requiring a certain type of new knowledge produced in a certain field of study particularly tend to co-locate with HEIs in that same field. Thus industries that innovate through process innovation (e.g., supplier-dominated services) co-locate with HEIs conducting applied research, whereas industries characterized by radical innovations (e.g., science-based manufacturing) require initial inputs from HEIs conducting basic research (Bonaccorsi et al., 2013; Cohen et al., 2002; Miller et al., 2005). Moreover, the different innovation patterns across industries also affect the propensity of knowledge from HEIs to lead to an increase in regional firm location. Shane (2001) shows that more radical inventions linked to academic university knowledge are more likely to be commercialized through the creation of a new firm.

Third, whether or not a firm can profit from co-location with an HEI depends on industry-specific human capital needs. Baptista and Mendonça (2010) argue that specialized human capital is particularly important for firm location in high-tech industries. Empirical evidence shows that for high-tech firms, proximity to a university in the natural sciences (with more specific human capital) is more important than proximity to a university in the social sciences (with more general human capital) (Audretsch et al., 2004; Fritsch and Aamoucke, 2017). The inverse holds for knowledge-intensive business service activities that particularly depend on the more general human capital created by academic universities specializing in the social sciences (Cassia and Colombelli, 2008).

Two arguments from different strands of the economic literature also apply here. On one hand, the entrepreneurship literature focusing on firm location in the form of start-ups emphasizes the importance of entrepreneurial human capital and the

necessity of both scientific and entrepreneurial human capital for positive effects on firm location (Muscio et al., 2021; Qian et al., 2013). This argument is in line with Lazear's 2004 idea that entrepreneurs are generalists, not technical specialists. Thus HEIs specializing in the social sciences might be necessary for transferring new knowledge into economic knowledge. On the other hand, the regional economic literature argues that diversity in a region's human capital positively impacts new firm formation (Glaeser et al., 1992; Hülsbeck and Pickavé, 2014; Rosenthal and Strange, 2003), and that firms, when they mature, tend to move to regions with industry-specific human capital (Rosenthal and Strange, 2004). Thus the regional impact on firm location of HEI-produced human capital in different fields of study is not clear per se.

Despite the large body of theoretical and empirical literature focusing on the impact of HEIs on regional firm location, three research gaps regarding effect heterogeneity remain. These gaps are critical when examining how different types of HEIs in different fields of study affect firm location across different manufacturing and service industries. Knowing these heterogeneous effects is essential and highly relevant for HEI policies that intend to match the regional establishment of HEIs with regional economic and industry backgrounds.

The first research gap concerns the output of different types of HEIs. While the literature focuses mainly on academic universities, which produce predominantly basic knowledge, evidence for the effects of applied HEIs on regional firm location across different industries is missing. However, as we discuss in Section 3, applied HEIs differ significantly from academic universities concerning their students (background in vocational education) and their research focus (more applied research). Therefore, the impact of applied HEIs on regional firm location is likely

to differ significantly from that of academic universities. An exception regarding the analysis of such applied HEI is the paper by Fritsch and Aamoucke (2013), who find—inter alia—a positive effect of German UASs on innovative start-ups. Yet, their dataset neither allows them to distinguish UASs in different fields of study nor to distinguish a broad set of industry categories in which regional firm location possibly would occur. Closing this research gap is vital for policy decisions regarding the ideal type of HEI for fostering regional firm location.

The second research gap concerns the different outputs of UASs across different fields of study. While the literature on the effects of academic universities on firm location shows vast differences between fields of study, empirical evidence for the effects of applied HEIs across different fields of study is inexistent to date. However, estimation results and effect patterns from academic universities are unlikely to be directly transferable to applied HEIs due to their different focus concerning teaching and research. Therefore, studying and revealing heterogeneous effects of applied HEIs across different fields of study becomes crucial for policy makers who have to decide on the specialization of new HEI that should match the knowledge needs of a local economy.

The third research gap concerns different knowledge inputs required by firms across industries. While most studies focus on some classification of high-technology manufacturing and service industries, regional firm location across other industries is mostly neglected. Yet focusing on the entire set of manufacturing and service industries is particularly important when UASs with their applied knowledge output are analyzed.

One exception that analyzes a broad set of manufacturing and service industries is the paper by Bonaccorsi et al. (2013), who introduced the detailed industry tax-

onomy that we use in our paper. However, their focus on academic universities, leaves the question on effects of UASs, i.e., applied HEIs, specializing in different fields of study on regional firm location across industries unanswered. Given that newly established HEIs nowadays focus more often on applied rather than academic research, closing this research gap is pivotal for future policy making.

Our study's main contribution is to simultaneously address these three research gaps. First, we focus on UASs, i.e., an understudied type of HEIs that conducts applied research and that is important for regional economic success in highly developed and innovative countries like Switzerland or Germany. Second, we analyze the complete set of fields of study these UASs specialize in because effects are likely very heterogeneous across fields and thus important to be considered in policy decisions. Third, we include the entire spectrum of manufacturing and service industry categories in our analysis, as industry affiliation is also crucial for heterogeneity in the effects of UASs on regional firm location. Thus, taken together, we are able to analyze the effects of UASs on regional firm location for a large set of detailed field and industry combinations.

Overall, both the theoretical arguments raised and the empirical evidence provided for the effects of HEIs on firm location in general do not point to a unique field-industry combination favorable for firm location. In contrast, the literature reveals that, for positively impacting firm location, HEI-produced knowledge outputs from a certain field of study must match the regional knowledge inputs that firms in a certain industry need (Landry et al., 2007). Thus, for our analysis of the establishment of UASs in Switzerland, investigating which UAS specializing in a particular field of study positively affects firm location in which industries calls for an *empirical* analysis.

3. Institutional Background on UASs in Switzerland

Starting in 1997, a new type of tertiary education institution was established in Switzerland—the UASs. These UASs are by law "equal, but different" from academic universities. UASs and academic universities differ in several dimensions, whereof two are essential for our analysis and need to be explained here.

First, while students of academic universities mainly come from a general education track ("Gymnasium") and continue an academic education at university, students of UASs typically come from vocational education and training (VET, "berufliche Grundbildung") and have completed a vocational baccalaureate ("Berufsmaturität"). Thus, these students already have hands-on professional skills and labor market experience. Furthermore, UAS students often worked in regional firms before their studies and know the corresponding industry and prevailing processes and products well before starting at a UAS (SCCRE, 2018). At UASs, these students combine their practical skills and industry knowledge with an applied academic education during their bachelor's degree (Backes-Gellner and Pfister, 2019). Second, while academic universities conduct basic research, UASs have a legal mandate to conduct applied research and to collaborate with the regional economy (Pfister et al., 2021), thereby contributing to regional development.

Given the particular skill mix and the strong focus on applied research taught at UASs, integrating UAS graduates into local firms is relatively easy. One year after graduation, 90% of graduates are employed (SCCRE, 2018). Once integrated, UAS graduates function as bridge-builders between middle-skilled workers with VET degrees and academic university graduates (Schultheiss et al., 2022). Moreover, Lehnert et al. (2020b) show that the skills of UAS graduates are valuable

for small firms by allowing these firms to pick up or expand their R&D activities. As for the legal mandate to conduct applied research, Arvanitis et al. (2008) find that UASs indeed have an above-average propensity to engage in knowledge and technology transfer activities with the local economy, compared to academic universities. Therefore, the particular skill mix and the strong focus on applied research of UASs is presumably also favorable for regional firm location. However, what remains unclear so far, is whether this holds equally well across different fields of study of UASs.

Regarding the generalizability of our results, international comparisons of UASs across European countries (i.e., Belgium, the Czech Republic, Finland, Germany, the Netherlands, and Norway) find that Swiss UASs are closest to UASs in the Netherlands, Finland, and Germany (Lepori and Kyvik, 2010). UASs in these countries share in particular the goal to "[...] educate a profession-oriented workforce and use technology transfer and applied research to enhance regional development" (Starnecker and Wirsching 2022, p. 171). Therefore, the results of our study will be of particular interest to UASs in these countries. However, in many countries, UASs experience a strong convergence towards the profiles of academic universities (Schüll, 2019). Thus, our empirical evidence for Switzerland, with its divided system between UASs and academic universities, may not reflect the actual effects in other countries with systems where UASs and academic universities converge. Our results emphasize the importance of more strongly considering the particularities in the profiles of UASs in future systemic decisions on higher education systems within and across countries.

4. Field and Industry Categories and Data Sources

To analyze the heterogeneous effects of the establishment of UASs in different fields on firm location in different industries, we use two datasets. First, the data on the timing and location of UASs specializing in different fields—allowing us to construct treatment and control groups—is self-collected data. For categorizing the UASs into fields, we follow the official classification of the Swiss federal government (EAER, 2014). Second, for our outcome variables, i.e., firm location, we use data from the Swiss business census, provided by the Swiss Federal Statistical Office (SFSO). Drawing on an industry taxonomy suggested by Bonaccorsi et al. (2013), we divide firms into different industries according to the knowledge inputs they need and the prevailing innovation patterns they pursue.

4.1. Timing and location of UASs in different fields

From 1997 through 2020, 157 UASs in 55 municipalities were established in Switzerland.[6] According to the EAER (2014) classification, these UASs offer a wide range of tertiary degree programs in 12 fields of study. Table 3 in Appendix A lists the programs in each field of study. In contrast to academic university campuses, a UAS campus often covers only one field of study.

Our analysis focuses on UASs specializing in eight of the 12 fields of study: (1) Chemistry & Life Sciences, (2) Business, Management & Services, (3) Architecture, Construction & Planning, (4) Design, (5) Engineering & IT, (6) Music, Theater

[6]Technically, only seven UASs exist. These seven UASs are the umbrella organizations for different UAS campuses in different fields with different locations. However, throughout the study, we refer to a UAS as a "campus" in a particular field and municipality, because the campus is the entity whose effects on the regional economy we are investigating.

& other Arts, (7) Health and (8) Social Work.[7] Fig. 2 shows the location of the UASs specializing in all eight fields. Differently shaped markers indicate the years the UASs were established.[8]

To investigate the timing and location of the establishment of UASs in all fields, we draw on a variety of publications: degree program catalogs ("Fachhochschulführer"), official statistics on UAS students, UAS annual reports, accounts of accreditation bodies, and books on the establishment history of particular UASs.[9] We use these sources to investigate all degree programs offered by UASs. We consider a program reported in one of these publications as a UAS degree program in a particular field and year only after the corresponding UAS was institutionally accepted by the Swiss federal council, i.e., was obligated to conduct applied research.[10]

Given that UASs comprise different facilities and occasionally undergo spatial consolidations over time, we have to localize the UAS facilities for each field in each year. The location often has to be investigated through annual reports of UASs or with the help of newspaper articles. In sum, the 139 UASs specializing in

[7]We exclude UASs specializing in Agriculture & Forestry, because we have no data on potential outcomes, i.e., the number of firms in associated industries are not included in our data. We also exclude UASs specializing in Sports, Applied Linguistics and Applied Psychology, because of the small number of campuses and small number of observations, i.e., municipalities in proximity to UASs specializing in these fields.

[8]Fig. 2 shows UASs established only between 1997 and 2017, as this is the period we cover in our empirical analysis.

[9]Our main sources are degree program catalogues ("Fachhochschulführer") available for 1999, 2000, 2007 and 2008, published by official bodies such as the Swiss Conference of Cantonal Ministers of Education (EDK), the Federal Commission for Universities of Applied Sciences (EFHK), and the Conference of the Swiss Universities of Applied Sciences (KFH). To determine which degree programs are offered at UASs, we also use official statistics on UAS students by the SFSO.

[10]For UASs specializing in Chemistry & Life Sciences, Business, Management & Services, Architecture, Construction & Planning, Design and Engineering & IT, the first UASs were institutionally accepted in 1997. For UASs specializing in Music, Theater & other Arts, Health, and Social Work, only in 2005.

the eight fields of study we analyzed are situated in 53 municipalities.[11] This data allows us to construct treatment and control groups according to the proximity of a municipality to a UAS specializing in a particular field. For the assignment of municipalities to the treatment or control groups, we follow Pfister et al. (2021) by assigning municipalities to the treatment group of a UAS specializing in a particular field if they are within 25-km from this UAS.[12] Depending on the year and field of study of a UAS, the assignment to the treatment group results in 33% (Chemistry & Life Sciences) to 73% (Engineering & IT) of municipalities in a treatment group. Overall, 82% of all municipalities belong at least once to a treatment group (see Table 6 in Appendix B). Fig. 2 depicts the treatment and control groups for UASs specializing in different fields.

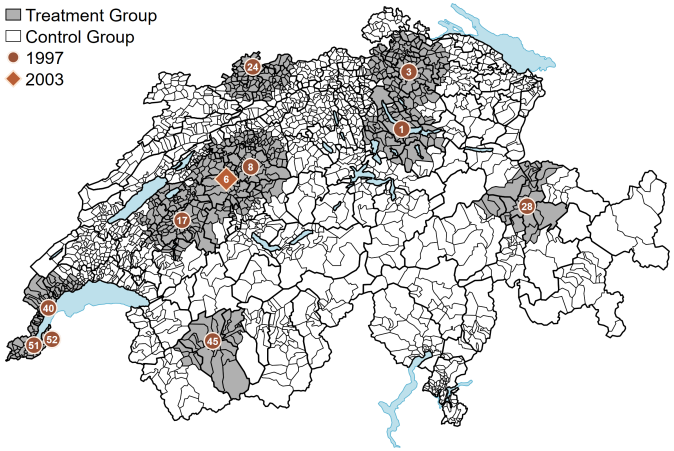
4.2. Data on firm location in different industries

For our outcome variables, the number of firms per municipality and industry category, we use the Swiss business census, which provides us with data on the number of firms at the municipality level, subdivided into different industries (NOGA classification).[13] The data is available for 1995, 1998, 2001, 2005, 2008, and 2011 through 2017. Thus our analysis period is 1995 through 2017, with several data gaps in between. In addition, the Swiss business census provides us with alterna-

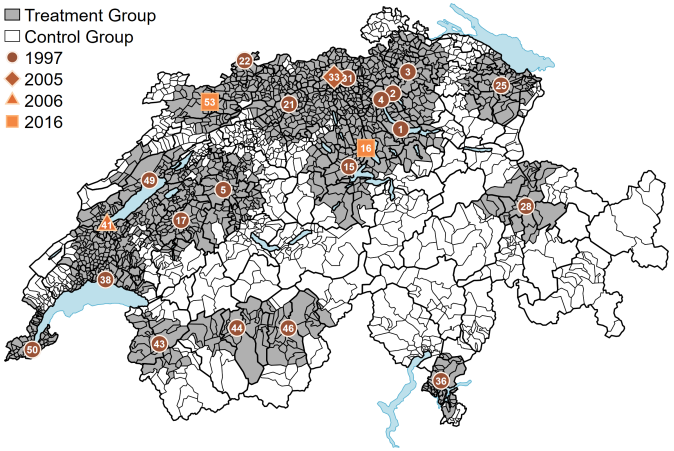
[11]The full dataset contains 157 UASs in 55 municipalities. Excluding UASs specializing in Agriculture & Forestry, Sports, Applied Linguistics and Applied Psychology and restricting the time period analyzed to 1995 through 2017 leave us with fewer observations.

[12]Pfister et al.'s (2021) argument for the 25-km radius is that it corresponds to the actual travel distance of around 90% of Swiss workers and thus appropriately captures UAS graduates as one source of knowledge. For knowledge spillovers from HEIs in general, empirical findings range from 20 kilometers (Andersson et al., 2004) to 120 kilometers (Acs et al., 2002).

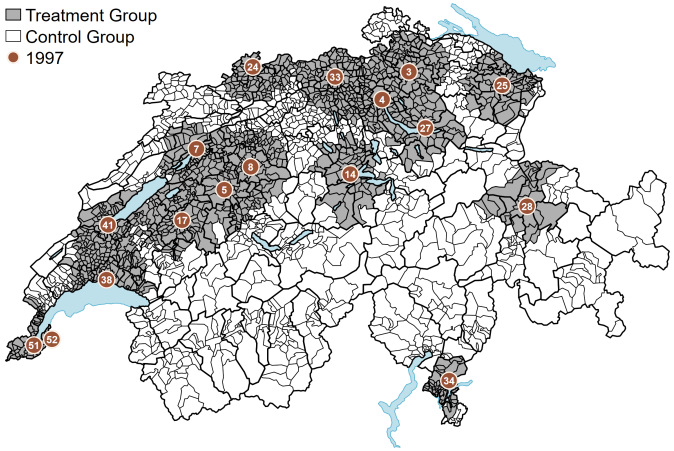
[13]The "Nomenclature générale des activités économiques" (NOGA) is the Swiss general classification of economic activities. It closely follows the NACE, which is the European Community classification of economic activities (SFSO, 2016a).



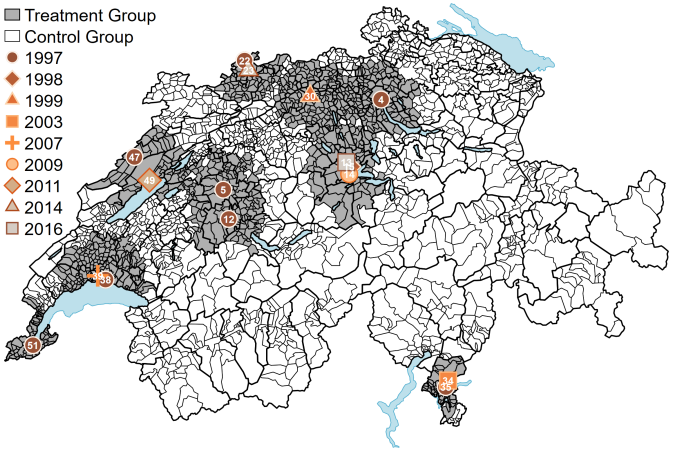
(a) *Chemistry & Life Sciences*



(b) *Business, Management & Services*

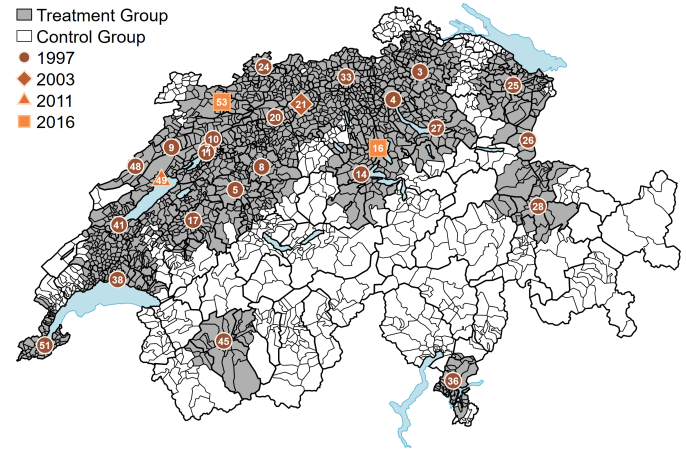


(c) *Architecture, Construction & Planing*

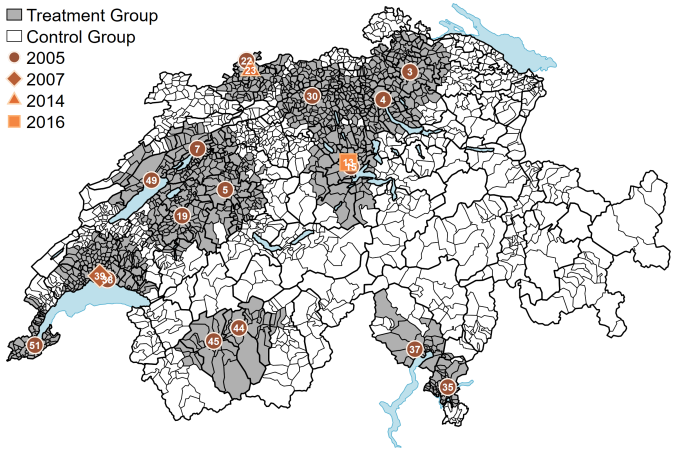


(d) *Design*

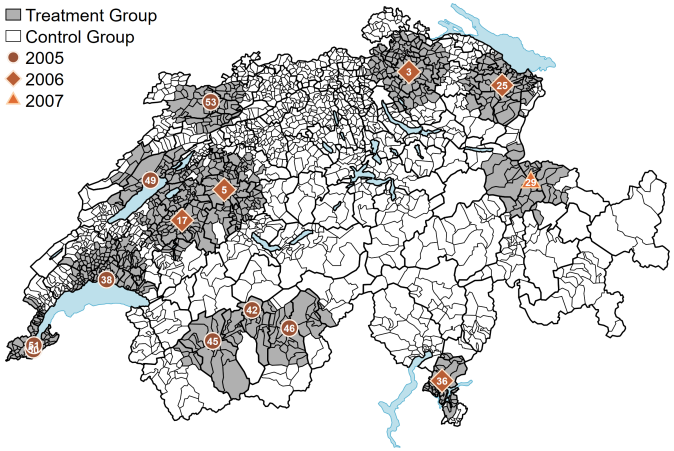
Notes: The maps show the UAS locations in all eight fields analyzed and the years 1997 through 2008. Treatment groups are indicated in dark gray, control groups in egghshell color. The numbers indicated refer to the municipalities the UASs are located in: (1) Wädenswil, (2) Dübendorf, (3) Winterthur, (4) Zürich, (5) Bern, (6) Zollikofen, (7) Biel/Bienne, (8) Burgdorf, (9) Saint-Imier, (10) Sauge, (11) Nidau, (12) Riggisberg, (13) Emmen, (14) Horw, (15) Luzern, (16) Risch, (17) Fribourg, (18) Givisiez,
(19) Granges-Paccot, (20) Oensingen, (21) Olten, (22) Basel, (23) Münchenstein, (24) Muttenz, (25) St. Gallen, (26) Buchs (SG), (27) Rapperswil-Jona, (28) Chur,
(29) Landquart, (30) Aarau, ...*continues on next page*



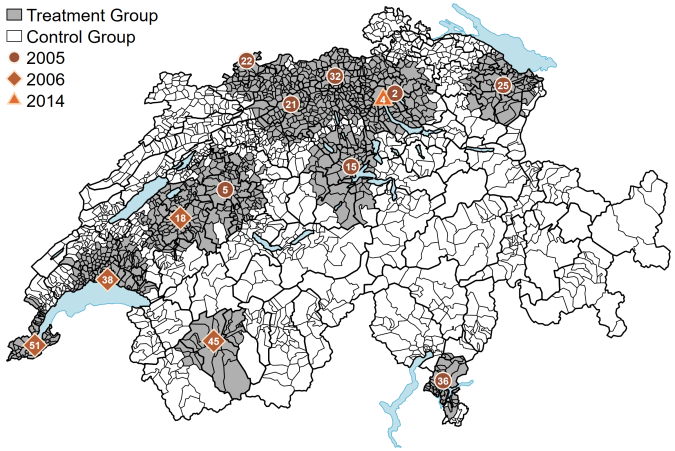
(e) *Engineering & IT*



(f) *Music, Theater & other Arts*



(g) *Health*



(h) *Social Work*

continuation from last page... (31) Baden, (32) Brugg, (33) Windisch, (34) Canobbio, (35) Lugano, (36) Manno, (37) Terre di Pedemonte, (38) Lausanne, (39) Renens (VD), (40) Nyon, (41) Yverdon-les-Bains, (42) Leukerbad, (43) Saint-Maurice, (44) Sierre, (45) Sion, (46) Visp, (47) La Chaux-de-Fonds, (48) Le Locle, (49) Neuchâtel,
(50) Carouge (GE), (51) Genève, (52) Jussy, (53) Delémont.

Figure 2. UAS locations by field and establishment year

tive outcomes, such as the number of firms in different groups, according to firm size—data that we use for further analyses and robustness checks.

The missing piece for analyzing the heterogeneous effects on firm location in different industries of UASs specializing in different fields of study is a taxonomy of industries according to their knowledge needs and prevailing innovation patterns. To construct an industry taxonomy, we rely on Bonaccorsi et al. (2013), who use classifications by Pavitt (1984) for manufacturing industries, and by Miozzo and Ramirez (2003) for service industries and summarize these classifications into a taxonomy with eight industry categories.

Using this taxonomy is appropriate for two reasons. First, the industry taxonomy is precisely designed to reflect firms' different knowledge requirements, i.e., knowledge sources, innovation patterns, and human capital needs. These different knowledge requirements in turn are a potential source of heterogeneity in the effects of UASs on regional firm location. Therefore, using this taxonomy allows us to estimate industry-specific heterogeneity in the effects of UASs that are linked to differences in the required knowledge inputs.

Moreover, an advantage of this taxonomy is, that it is based on the NACE ("nomenclature statistique des activités européenne"), i.e., the industry standard classification used in the EU to represent *all* manufacturing and service sectors. Since firms in our data are also assigned to industries based on the NACE, we are able to fully represent this firm taxonomy with our data. In so doing, we can analyze effects of UASs on the universe of manufacturing and service firms, without neither excluding industries with particular knowledge requirements, nor making assumptions or industry category assignments that contradict theoretical considerations.

Second, using the same taxonomy as Bonaccorsi et al. (2013), who analyzed a similar research question, allows us to add to their findings in particular, and the literature on heterogeneity of knowledge spillovers from HEI in general, by expanding the analysis to another type of HEI as well as a different country context. Analyzing a different type of HEI—i.e., UASs that focus on applied research as opposed to academic universities that focus on basic research—is important for future research to better understand whether, and if so, how the type of knowledge produced by a HEI influences regional firm location. From a policy perspective, learning about differences in the regional economic effects of applied research is crucial for designing regional innovation systems.

In this taxonomy, Bonaccorsi et al. (2013) subdivide the manufacturing industries into (1) science-based, (2) supplier-dominated, (3) scale-intensive, and (4) specialized-supplier manufacturing. For service industries, Bonaccorsi et al. (2013) subdivide industries into (1) knowledge-intensive business services, (2) supplier-dominated services (3) physical network services and (4) information network services.

Table 1 summarizes how these industry categories differ in their prevalent innovation patterns and knowledge needs, gives several examples of industries belonging to each category, and provides some descriptive statistics for the structure and development of each industry category over time. In addition, Table 5 in Appendix B shows the assignment of the 88 different industries to the eight industry categories.

For each year and municipality, we calculate the number of firms in the eight industry categories, following Bonaccorsi et al.'s (2013) taxonomy. Table 4 in Appendix B shows descriptives for the eight industries, revealing, first, that mu-

nicipalities in the treatment group have on average more firms. Second, the two smallest industry categories in terms of number of firms are science-based manufacturing and specialized-supplier manufacturing (both with around one firm per municipality on average). The largest industry categories are supplier-dominated services (96 firms per municipality) and know-ledge-intensive business services (45 firms per municipality).

4.3. Data on Control Variables

To account for time-variant municipality characteristics that could simultaneously affect UAS establishment and firm location (see Section 5.1), we were able to collect data from three additional data sources: data on population density, data on gross floor space use, and data on daytime satellite data. First, based on yearly data provided by the SFSO (2016b; 2020), we calculate the population density by dividing the average population of a municipality by the area of the municipality. Second, we use data on the square meters in gross floor space used for infrastructure buildings at the municipality level, data provided by Wuest Partner, which collects this data from building insurance companies. In so doing, we follow Bonaccorsi et al. (2013), who chose a similar strategy by controlling for the regional economic infrastructure using an index.

Third, we use daytime satellite data to control for regional economic activity (Lehnert et al., 2020a). The advantage of satellite data is its availability at a highly disaggregated regional level and for periods when no other municipality-level data on economic activities is available. Lehnert et al.'s (2020a) data comes from the algorithm they developed. For each municipality, the data contains information

on six surface groups: (1) built-up land, e.g., buildings; (2) grass; (3) forests; (4) cropland; (5) land without vegetation, e.g., rocks or ice; and (6) water. To account for regional time-varying differences, we include these surface groups in our regression analysis.[14]

Combining all these data sets, we have 2,222 observations per year (all Swiss municipalities as of 2018[15]) over 12 years—a total of 26,664 observations—that we can use for our empirical analysis.

[14]In using forest as the base group, we follow Lehnert et al. (2020a).

[15]To account for municipality mergers over time, we updated all years to the stock of municipalities in 2018.

Table 1: Industry taxonomy according to knowledge inputs needed by firms and descriptive statistics by industry category

Manufacturing Industries		
Science-based manufacturing		
Characteristics:	Firms are characterized by radical product innovations resulting from exploiting knowledge created by higher education institutions—predominantly in basic research. The uncertainty associated with exploiting new knowledge economically, makes it especially appropriate for new or small firms, because incumbent firms suffer of organizational inertia and path dependencies.	
Examples:	Pharmaceutical, optical and computer industries.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	1.1 firms
	Trends number of firms (1995-2017):	-0.3 firms (-22%)
	Composition regarding firm size (1995-2017):	Micro: 56.5%; Small 25.5%; Medium 13.8%; Large 4.2%
	Average number of startups (2013-2017):	0.04 startups
Supplier-dominated manufacturing		
Characteristics:	This category covers more traditional industries with innovations stemming mostly from cost-reducing process innovations pushed forward by suppliers of new equipment rather than by firms themselves. The link to both basic or applied knowledge from higher education institutions is rather weak.	
Examples:	Manufacturing of textiles and furniture.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	7.7 firms
	Trends number of firms (1995-2017):	-0.4 firms (-6%)
	Composition regarding firm size (1995-2017):	Micro: 84.9%; Small 12.7%; Medium 2.2%; Large 0.3%
	Average number of startups (2013-2017):	0.4 startups
Scale-intensive manufacturing		
Characteristics:	For firms, exploiting economies of scales is crucial. Thus nevertheless in-house developed process innovations that allow for up-scaling are the main source of innovation, firms also rely on applied knowledge particularly in engineering.	
Examples:	Food and beverage production, metal products, car industry.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	6.7 firms
	Trends number of firms (1995-2017):	+0.2 firms (+3%)
	Composition regarding firm size (1995-2017):	Micro 69.9%; Small 23.2%; Medium 5.9%; Large 1.0%
	Average number of startups (2013-2017):	0.3 startups
Specialized-supplier manufacturing		
Characteristics:	Knowledge in these firms is mainly created by incremental product engineering and feedback of equipment users. However, firms also exploit knowledge from higher education institutions in applied sciences and engineering.	
Examples:	Manufacturing of electrical and machinery equipment.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	1.6 firms
	Trends number of firms (1995-2017):	-0.8 firms (-36%)
	Composition regarding firm size (1995-2017):	Micro 58.8%; Small 26.8%; Medium 11.6%; Large 2.8%
	Average number of startups (2013-2017):	0.04 startups

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Service Industries		
Knowledge-intensive business services		
Characteristics:	Firms are characterized by radical service innovations and derive their innovative capacity from both internal and external knowledge. Thus a strong link to both basic and applied knowledge from higher education institutions exists.	
Examples:	Programming, architectural and engineering activities, R&D.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	44.5 firms
	Trends number of firms (1995-2017):	+34.2 firms (+144%)
	Composition regarding firm size (1995-2017):	Micro 92.8%; Small 6.3%; Medium 0.8%; Large 0.1%
	Average number of startups (2013-2017):	5.2 startups
Supplier-dominated services		
Characteristics:	Firms are predominantly shaped by process innovations, i.e., automation and digitization, and by the investment in capital goods produced by the manufacturing sector. Links to higher education institutions are rather weak.	
Examples:	Accommodation, real estate, education, human health services.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	96.4 firms
	Trends number of firms (1995-2017):	+40.8 firms (+55%)
	Composition regarding firm size (1995-2017):	Micro: 87.8%; Small 10.1%; Medium 1.8%; Large 0.3%
	Average number of startups (2013-2017):	7.9 startups
Physical network services		
Characteristics:	Firms are characterized by competitive advantages through large networks that are efficiently maintained by process innovations. While firm location in these industries is driven by availability of physical networks, knowledge in applied sciences and business is advantageous to manage process innovations.	
Examples:	Transportation, electricity, water.	
Descriptives: (by municipality)	Average number of firms (1995-2017):	24.9 firms
	Trends number of firms (1995-2017):	+0.7 firms (+ 3%)
	Composition regarding firm size (1995-2017):	Micro 83.8%; Small 13.4%; Medium 2.5%; Large 0.4%
	Average number of startups (2013-2017):	1.6 startups
Information network services		
Characteristics:	Firms are characterized by competition that focuses on economies of scales, where efficient information processing is key. Innovation is achieved both through process and product innovations. However, digitization led to outsourcing of information-based innovation to other industries, thereby lowering the necessity of technological knowledge but increasing the importance of business knowledge within the industry.	
Examples:	Financial and insurance services, publishing activities	
Descriptives: (by municipality)	Average number of firms (1995-2017):	8.4 firms
	Trends number of firms (1995-2017):	+3.2 firms (+50%)
	Composition regarding firm size (1995-2017):	Micro 83.2%; Small 13.1%; Medium 2.9%; Large 0.8%
	Average number of startups (2013-2017):	0.9 startups

Source: Taxonomy based on Bonaccorsi et al. (2013); Miozzo and Soete (2001); Pavitt (1984). Descriptives on firms based on business census. Firm sizes: microfirms, 1-9 employees; small firms, 10-49 employees; medium firms, 50-249 employees; large firms, 250+ employees. Descriptives on start-ups based on the firm demography statistics from the SFSO.

5. Empirical Strategy

5.1. Addressing Potential Endogeneity

When estimating the impact of the establishment of a UAS specializing in a field on the number of firms in an industry, we need to control for potential endogeneity in the establishment of UASs. While Pfister et al. (2021) and Lehnert et al. (2020b), analyzing the impact of UASs specializing in STEM on innovation and R&D employment, show that the establishment of these UASs was quasi-random, this argument might not apply to UASs specializing in fields other than STEM. At least two factors challenge the assumption of exogeneity in the establishment of UASs specializing in non-STEM fields.[16]

First, Pfister et al. (2021) argue that the location of UASs specializing in STEM fields was quasi-random, because after the federal government mandated regional consolidation of degree programs to ensure sufficiently large cohorts, continuing political discussions made the location of certain fields of study unpredictable. However, such consolidations took place on a much lower scale for UASs specializing in Business, Management & Services, for which fewer small degree programs needed consolidation. Therefore, UASs in these fields were sometimes kept in regions where UASs in other fields were closed because the cohorts were too small. The aim of this strategy was to reach political compromise across regions negatively affected by the consolidations of UASs in particular fields—with the consequence that UASs specializing in Business, Management & Services more often survived.[17]

[16] In our case, a further impediment to exploiting standard empirical methods, such as a difference-in-differences, is the data structure. As we only have few pretreatment observations, finding support for parallel trends is not feasible.

[17] The UAS of Northwestern Switzerland constitutes a good example: While, after several years of discussion, the involved regions agreed to concentrate Engineering & IT in one region

Second, UASs specializing in Music, Theater & Other Arts, Health, and Social Work were approved by the federal government only in 2005, with the approval linked to the explicit requirement that these newly approved UASs were integrated into existing ones (Bundesrat, 2003). Therefore, the location of UASs specializing in Music, Theater & other Arts, Health, and Social Work was not quasi-random but dependent on the existence of previously established UASs.

To account for such potential endogeneities in the establishment of some UASs, we run two-way fixed effects estimations. We include municipality fixed effects to account for time-invariant municipality characteristics influencing both the establishment of UAS and regional firm location. By including year fixed effects, we control for common time trends of municipalities. To control for time-variant municipality characteristics that could simultaneously affect the establishment of UASs and regional firm location, we first control for the population density, to account for agglomeration economies (Baptista and Mendonça, 2010; Bonaccorsi et al., 2013).

Second, we control for a region's infrastructure by including the square meters in gross floor space used for infrastructure buildings at the municipality level.[18] Third, we use daytime satellite data to control for regional economic activity at the municipality level (see Section 4.3), as suggested by Lehnert et al. (2020a). They extensively show for Germany that the data reliably predicts changes in regional economic activity over time.

Additional to systematic differences across municipalities in the treatment and control groups that we address with our battery of control variables, our empirical

and Chemistry & Life Sciences in another (resulting in the relocation of several degree programs), three of four regions still offered degree programs in Business, Management & Services—often because these locations had predecessor institutions in business (NZZ, 2005).

[18]Earlier studies applied similar control strategies by including an index of economic infrastructure (Bonaccorsi et al., 2013).

strategy could yield misleading results due to reverse causality. In our case, reverse causality would mean that UASs are systematically established in regions with historically higher growth rates in the number of firms. In such a case, empirically found positive effects of the establishment of UASs on regional firm location would be driven by this initial difference in growth rates rather than reflecting a true increase in regional firm location due to the establishment of a UAS.

To provide descriptive evidence against this reverse causality argument,[19] we compare average growth rates in the number of firms across treatment (pre-treatment and post-treatment) and control groups. Similar growth rates in the control group and the treatment group prior to the treatment would speak against reverse causality. Figs. 4 through 7 in Appendix B depict these growth rates separately for each field-industry combination. Throughout all field-industry combinations, comparisons of the average growth rate in the number of firms for the control group (diamond symbol) and the pre-treatment average growth rate in the number of firms for the treatment group (circle symbol), show no systematical patterns of differences between these average growth rates (vertical lines indicate confidence intervals). Therefore, our empirical strategy, i.e., estimating a fixed-effects regression (outlined in Section 5.2), is well-suited for analyzing the effect of the establishment of UASs on regional firm location across different field-industry combinations.

5.2. Estimation Strategy

Analyzing different field-industry combinations, we estimate the following regression equation separately for each of the eight UAS fields of study and the eight industry categories:

[19] We also run an empirical robustness check addressing reverse causality in Section 6.4.

$$
\begin{aligned}
y_{it}^{m} =& \alpha + \beta \mathrm{UAS}_{i(t-2)}^{k} + \delta \mathrm{UAS}_{i(t-2)}^{l \neq k} \\
&+ \boldsymbol{x}_{i(t-1)}' \boldsymbol{\rho} + \tau_t + \phi_i + \mu_{it},
\end{aligned} \tag{1}
$$

with i = municipality, t = year, m = industry category and k = UAS field. Thus y_{it}^{m}, the outcome of interest, represents the number of firms in municipality i and year t in industry category m. The variable $\mathrm{UAS}_{i(t-2)}^{k}$ indicates the treatment. It is a dummy that equals 1 in periods in which a municipality i is within the 25-km radius from a UAS specializing in field k. However, the $(t-2)$ subscript indicates that the treatment is lagged by two years to account for the time it takes for both knowledge and human capital produced by UASs to spill over to the regional economy.[20] The coefficient of interest is thus β. It shows the effect on the number of firms in industry category m associated with a newly established UAS specializing in field k.

In contrast, the term $\mathrm{UAS}_{i(t-2)}^{l \neq k}$ takes the value 1 in all periods where a municipality is within 25 km of a UAS specializing in another field l. This dummy variable thus controls for potential effects of nearby UASs specializing in other fields as well as for the fact that UASs can specialize in more than one field of study. The vector $\boldsymbol{x}_{i(t-1)}'$ contains our controls for population density, strength of regional infrastructure and regional economic activities (see Section 4.3). We

[20] By lagging the treatment, we follow Pfister et al. (2021), who argue that the first effects are expected when UAS graduates first enter the regional labor market. They are expected to do so three years after their UAS is established, corresponding to the usual duration of a bachelor program. However, our data structure differs from that of Pfister et al. (2021), because we have some gaps between the years (see Section 4.2). Therefore, we lag the treatment by two periods and ensure that—depending on the UAS establishment year—the treatment effect is lagged by between two to four periods. Table 8 in Appendix B reports the lags that result from our 2-year lag assumption in combination with the outcome data structure.

lag these control variables by one period to avoid simultaneity problems, thereby following a standard procedure in the analysis of knowledge spillovers from HEIs (e.g., Cowan and Zinovyeva 2013).[21] τ_t are year effects, ϕ_i are municipality fixed effects, and the error is represented by μ_{it}=$\nu_i + \eta_{it}$ and thus clustered at the municipality level.

We estimate Equation (1) using a Poisson pseudo-maximum likelihood (PPML) estimator. In so doing, we take into account two characteristics in our dataset—heteroskedasticity and large amounts of zero values in the outcome variables—that make standard OLS estimation inappropriate (Santos Silva and Tenreyro, 2006). For some industry categories (e.g., science-based or spec-ialized-supplier manufacturing), we face large amounts of zero observations (see Table 7 in Appendix B). For these observations, the natural log would not be defined. Using a PPML estimator where we can include absolute values of our outcome variables and still interpret results as semi-elasticities solves this problem. Furthermore, the PPML estimator remains consistent in the presence of over-dispersion (Fally, 2015), which exists in our data. With all these advantages, the PPML estimator is the appropriate estimator for our data structure.[22]

[21] Different from the data we use for our outcomes of interest, data for control variables is available yearly, making a one-year lag feasible.

[22] To estimate PPML estimators with two-way fixed effects, we use the Stata command ppmlhdfe suggested in Correia et al. (2019a) and publicly available at `https://github.com/sergiocorreia/ppmlhdfe`.

6. Results

6.1. Summary of the Main Findings

The goal of our main analysis is to empirically determine which field-industry combinations have a (positive) effect on firm location. The results of this analysis appear in Table 2, which shows the results of separate regressions of Equation (1) by UAS fields of study (rows) and industry categories of firms (columns).[23],[24] For clarity, significant estimation results for field-industry combinations are indicated in bold. To account for multiple hypotheses testing, we report "sharpened false discovery rate q-values" as suggested by Anderson (2008), instead of the standard p-values.[25]

Table 2 reveals four broad patterns that we discuss in further detail in Section 6.2. First, UASs specializing in Chemistry & Life Sciences have no effects on firm location across manufacturing industries and significant positive effects on all service industries except physical network services. Second, UASs specializing in Business, Management & Services are favorable for firm location in all service

[23]To analyze which set of control variables—municipality and year fixed effects, population density, land use, infrastructure strength, or nearby UASs specializing in other fields—is appropriate for addressing the trade-off between goodness-of-fit and underfitting of the model, we estimate Equation (1) for all different fields of UASs and include the control variables step-by-step. Tables 9 through 16 in Appendix C show the results of these analyses. The commonly used model-comparison statistics support the model with the full set of controls because the inclusion of more controls lowers the Akaike information criterion (AIC), the Bayesian information criterion (not reported here), and increases the log likelihood (Cameron and Trivedi, 2009). Therefore, in the remainder of our analysis, we use the model with the full set of control variables (as shown in column 7 of Tables 9 through 16 in Appendix C).

[24]As a robustness check for our estimation strategy, we follow Bonaccorsi et al. (2013) and re-estimate our regression including UAS campuses in all different fields in one regression, with firm location in the eight different industry categories as the outcomes. The results of this robustness test appear in Table 17 in Appendix D, and look very similar to our main estimation specification.

[25]Table 19 in Appendix C also reports normal p-values and p*-values adjusted by the more conservative Bonferroni correction (Abdi, 2007).

industry categories except knowledge-intensive business services, whereas we find no effects on manufacturing industries.

Third, for UASs specializing in fields with a strong focus on engineering (Architecture, Construction & Planning, Design, and Engineering & IT), we find only very few significant positive effects on firm location, i.e., in supplier-dominated and in physical network service industries. In contrast, UASs specializing in Design and Engineering & IT have a significant and negative effect on firm location in some manufacturing industries, i.e., scale-intensive and specialized supplier manufacturing.

Fourth, UASs specializing in fields linked to the humanities (Music, Theater & other Arts, Health and Social Work) have significant positive effects on supplier-dominated services. However, potentially negative effects on firm location in specialized supplier manufacturing are also found for UASs specializing in Music, Theater & other Arts.

6.2. Interpretation of the Main Findings

6.2.1. UASs Specializing in Chemistry & Life Sciences

The positive and significant effect of UASs specializing in Chemistry & Life Sciences on knowledge-intensive business services shows that these UASs provide the applied knowledge needed for the radical service innovations that characterize firms in knowledge-intensive business services.[26] The increase of 8% in the number of firms in treated municipalities compared to municipalities in the control group is not only statistically, but also economically significant.

Similarly, the positive and significant effect of UASs specializing in Chemistry & Life Sciences on supplier-dominated services can be explained by a match in the hu-

[26] As this industry category also includes the industry "scientific R&D", our finding is in line with those of Lehnert et al. (2020b), who find positive effects of UASs specializing in STEM on

Table 2: PPML regression results of firm location in all industry categories on UASs in all fields

	Manufacturing				Services			
	Science-based	Supplier-dominated	Scale-intensive	Specialized supplier	Knowledge-intensive	Supplier-dominated	Physical network	Information network
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemistry & Life Sciences								
Effect	0.0915	0.0293	0.0298	-0.0216	**0.0767*****	**0.0443****	0.0306	**0.2666*****
q-value	0.1200	0.1550	0.1550	0.6370	0.0040	0.0400	0.2290	0.0070
Business, Management & Services								
Effect	0.0192	-0.0062	-0.0237	-0.0064	0.0128	**0.0712*****	**0.0583****	**0.3798*****
q-value	0.7410	0.7330	0.3700	0.8130	0.6480	0.0010	0.0360	0.0010
Architecture, Construction & Planning								
Effect	-0.0485	-0.0036	-0.0331	-0.0483	-0.0230	0.0046	**0.0457***	0.0555
q-value	0.3830	0.7620	0.1490	0.2670	0.2290	0.7330	0.0970	0.3700
Design								
Effect	0.0213	-0.0075	-0.0337	**-0.0921****	-0.0414	**0.0366***	0.0093	0.0362
q-value	0.6800	0.6800	0.1010	0.0360	0.1550	0.0740	0.7330	0.7330
Engineering & IT								
Effect	-0.0991	-0.0115	**-0.0481***	**-0.1053***	**-0.0984*****	0.0197	0.0135	-0.1263
q-value	0.1540	0.6480	0.0700	0.0970	0.0040	0.5190	0.7330	0.4360
Music, Theater & other Arts								
Effect	-0.0530	0.0108	-0.0262	**-0.1258*****	-0.0259	**0.0372***	-0.0044	-0.0386
q-value	0.4360	0.5500	0.1550	0.0010	0.3700	0.0500	0.8130	0.7330
Health								
Effect	0.0128	-0.0048	-0.0096	-0.0696	-0.0102	-0.0210	-0.0225	-0.1182
q-value	0.7410	0.7330	0.6480	0.1200	0.6930	0.2670	0.5500	0.2420
Social Work								
Effect	-0.0447	-0.0215	-0.0283	-0.0525	-0.0150	**0.0291***	0.0076	-0.0146
q-value	0.4360	0.2090	0.1490	0.1550	0.5500	0.0770	0.7330	0.8170
n	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
N	26,664	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows results of separate regressions of Equation (1). Rows correspond to UASs by fields; columns, to industry categories. For clarity, significant coefficients are in bold and significance levels are indicated as follows: * $q<0.10$, ** $q<0.05$, *** $q<0.01$. To control for multiple hypotheses testing, the reported q-values are "sharpened false discovery rate q-values" as suggested by Anderson (2008). Table 19 in Appendix C also reports normal p-values and p*-values adjusted by the more conservative Bonferroni correction (Abdi, 2007). All regressions include municipality and year fixed effects, and control for population density, land use, the strength of regional infrastructure, and nearby UASs specializing in other fields. n represents the number of municipalities; N, the overall observations. Table 6 in Appendix B reports the number of observations separated by fixed effects in the PPML estimation.

man capital that these UASs produce with the knowledge needs of firms in supplier-dominated services. On one hand, UASs specializing in Chemistry & Life Sciences have programs in food technology, oenology, and life science technologies—all educational degrees important to supplier-dominated services (e.g., food and beverage services, human health services). On the other hand, a considerable number of graduates from UASs specializing in Chemistry & Life Sciences later work in (tertiary) education (SFSO, 2005), an industry that is also comprised in supplier-dominated services.

The positive and large effect of UASs specializing in Chemistry & Life Sciences on information network services (30.6%) is—prima facie—surprising. However, this large effect size must be interpreted with the understanding that firm location in information network services is generally lower than that in knowledge-intensive business services or supplier-dominated services (see Table 1). Thus, in absolute terms, the impact on firm location in knowledge-intensive business services and supplier-dominated services associated with a UAS specializing in Chemistry & Life Sciences is actually larger. Therefore, an economically moderate effect on information network services is in line with earlier studies showing that the financial sector—the most important industry in this category—does not appear to attract many graduates or start-up founders from UASs specializing in Chemistry & Life Sciences (Barjak et al., 2020; SFSO, 2005).

The non-existing effects of UASs specializing in Chemistry & Life Science on firm location in manufacturing industries can be interpreted in two ways. First, for science-based manufacturing, the insignificant effect of these UASs on firm location indicates that these industries need basic, not applied, research, a finding

R&D employment and argue that these effects are partly driven by start-ups and younger firms.

also previously confirmed (Barra et al., 2021; Bonaccorsi et al., 2013; Klevorick et al., 1995). Second, for the remaining manufacturing industries, the missing effects on firm location are a recurring pattern across UASs specializing in all fields that appear to reflect a general development toward a more service-oriented economy, a pattern that we cover in detail when discussing the effects of UASs specializing in engineering.

Overall, the effects of UASs specializing in Chemistry & Life Sciences reveal important patterns that should be taken into consideration by policy-makers when deciding upon location decisions for such UASs. Establishing UASs specializing in Chemistry & Life Sciences should, according to our results, be most favorable for regional firm location in knowledge intensive-business and supplier-dominated services. In contrast, UASs specializing in Chemistry & Life Sciences are not a policy measure to foster regional firm location in manufacturing industries.

6.2.2. UASs Specializing in Business, Management & Services

For UASs in Business, Management & Services, the nature of the human capital that these UASs produce is general, which could explain why they are associated with positive effects only in the service industries that typically require more general skills (Silos and Smith, 2015)—but not in manufacturing industries that typically require more specific skills (Eggenberger et al., 2022). Moreover, the absence of effects on firm location in manufacturing industries is in line with the results from earlier studies. Neither Audretsch and Lehmann (2005b) nor Fritsch and Aamoucke (2017) find an effect of R&D or of students from academic universities in the social sciences on manufacturing firms. These findings indicate that manufacturing industries do not critically depend on knowledge outputs from Business, Management & Services.

Furthermore, we find that UASs in Business, Management & Services affect all service industry categories except knowledge-intensive business services. This pattern reveals that their outputs contribute to firm location more through process and product innovations than through radical service innovations. While process and product innovations are particularly important in supplier-dominated and physical network services, knowledge-intensive business services—for which we find no effect—are characterized by radical service innovations (see Table 1).

Regarding effect sizes, our results show that the positive impact on regional firm location associated with UASs specializing in Business, Management & Services is biggest (in relative terms) in the information network services (e.g., financial services, insurance services, or telecommunication activities). This industry category summarizes firms for which efficient information processing is crucial (Bonaccorsi et al., 2013). In a survey of UAS graduates, information network services are most frequently mentioned among graduates of UASs specializing in Business, Management & Services (Barjak et al., 2020). Thus, to access human capital needed by firms in the information network services, these firms can be expected to co-locate with UASs specializing in Business, Management & Services.

For policy makers, establishing UASs specializing in Business, Management & Services is in general a vital option to foster firm location in service industries. Establishing such UASs is particularly suitable to provide human capital and knowledge for service industries that innovate through process and product innovations.

6.2.3. UASs Specializing in Fields Linked to Engineering

The few positive and significant effects for service industries associated with UASs focusing more strongly on engineering (i.e., Architecture, Construction & Plan-

ning; Design; and Engineering & IT) can also be explained using Bonaccorsi et al.'s (2013) theoretical arguments. As an example: to maintain their infrastructure, firms in physical network services (e.g., transportation, electricity, or water) need knowledge provided by UASs specializing in Architecture, Construction & Planninng with degree programs such as architecture, civil engineering, construction management, or spatial planning.[27]

However, for the manufacturing industries, the absence of positive effects contradicts earlier findings. First, Fritsch and Aamoucke (2017) find positive effects for German UASs (independent of the field of study) on firm location in the manufacturing industries. Second, Woodward et al. (2006), Abramovsky et al. (2007), Kirchhoff et al. (2007), and Baptista and Mendonça (2010) find positive effects of academic universities in engineering on firm location in high-tech manufacturing industries.

Our result of non-existing positive effects of UASs specializing in fields linked to engineering on firm location in the manufacturing industries can be explained by at least two reasons. First, Silos and Smith (2015) show that graduates from HEIs specializing in engineering have very specific human capital focusing on quantitative and scientific skills. The very specific nature of this human capital thus makes them potentially less likely to exploit knowledge spillovers by means of establishing start-ups (Wagner, 2003). Second, Barjak et al. (2020) show that particularly UASs specializing in Architecture, Construction & Planning, and Engineering & IT often engage in contract research, which is not favorable for fostering firm loca-

[27]Furthermore, for UASs specializing in Architecture, Construction & Planning, emphasizing that Bonaccorsi et al. (2013) excluded the construction sector from their taxonomy is important. Estimating the effect of UASs specializing in Architecture, Construction & Planning on firm location in the construction industry results in a positive and significant increase of 3.5% in regional firm location (see Table 18 in Appendix D).

tion because the exploitation rights belong to the incumbent firm. Therefore, this mechanism might affect incumbent firms positively but firm location less strongly (Becker and Wagner, 2010).

As for the *negative* and significant effects on manufacturing firms associated with UASs in Design and Engineering & IT, they could represent the reinforcement of an otherwise existing and more general trend: In the period of the establishment of these UASs, Switzerland experienced a further tertiarization of the economy (Sheldon, 2005), for which the decreasing trend in the number of firms in manufacturing industries is a symptom (see Table 1). UASs specializing in engineering are likely to further stimulate this trend, because their graduates can more easily switch from manufacturing to service jobs (Schweri and Zbinden, 2009). The average growth in the number of firms depicted in Figs. 5 and 6 in Appendix B support this interpretation by revealing a reinforcement of an otherwise ongoing negative trend in the number of firms after the establishment of a UAS (particularly in specialized-supplier manufacturing).

Regarding policy suggestions, the pattern of our results shows that UASs specializing in fields linked to engineering are not particularly well-suited when regional firm location is the ultimate policy goal. However, these UASs can be an important policy instrument to accelerate the transformation towards a more service-oriented regional economy.

6.2.4. UASs Specializing in Fields Linked to Humanities

For UASs specializing in the broad fields of humanities (UASs specializing in Music, Theater & other Arts, Health, and Social Work), the detected positive effects in supplier-dominated services (e.g., education or human health services) correspond

with the finding that graduates of UASs specializing in Music, Theater & other Arts commonly work in education or cultural entrepreneurship (Barjak et al., 2020; SFSO, 2005). Moreover, graduates of UASs specializing in Social Work predominantly remain in human health services (SFSO, 2005). In contrast to these results, UASs specializing in Health have no effect on firm location whatsoever. This zero effect might be attributable to graduates of UASs specializing in Health having the lowest probability of starting a new firm (Barjak et al., 2020).

For policy makers, our results for UASs specializing in fields linked to humanities reveal an important insight. These UASs, provide human capital and knowledge for a very particular industry category, i.e., supplier-dominated services. Therefore, if fostering regional firm location in, e.g., education or human health services, is the policy goal, establishing UASs specializing in fields linked to humanities is a viable strategy.

6.2.5. Synthesis of Interpretation

Overall, the patterns in Table 2 illustrate, on one hand, that proximity to UASs specializing in Chemistry & Life Sciences and in Business, Management & Services is most favorable for firm location.[28] On the other hand, service industries profit on average more from a nearby UAS than manufacturing industries, whether a UAS specializes in a more technical or non-technical field. The industries that experience positive effects from UASs are predominantly characterized radical service innovations, incremental process innovations, or product innovations, but less often by radical product innovations. In a regional ecosystem, UASs and their

[28]This finding is also confirmed by a regression on the entire service industry: UASs specializing in Chemistry & Life Sciences increase firm location by 6.8% and UASs specializing in Business, Management & Services do so by 8.1% (see Table 18 in Appendix D).

applied knowledge outputs are thus an important complement to academic universities conducting basic research, thereby, providing knowledge inputs critical for radical product innovations.

6.3. Further Analysis

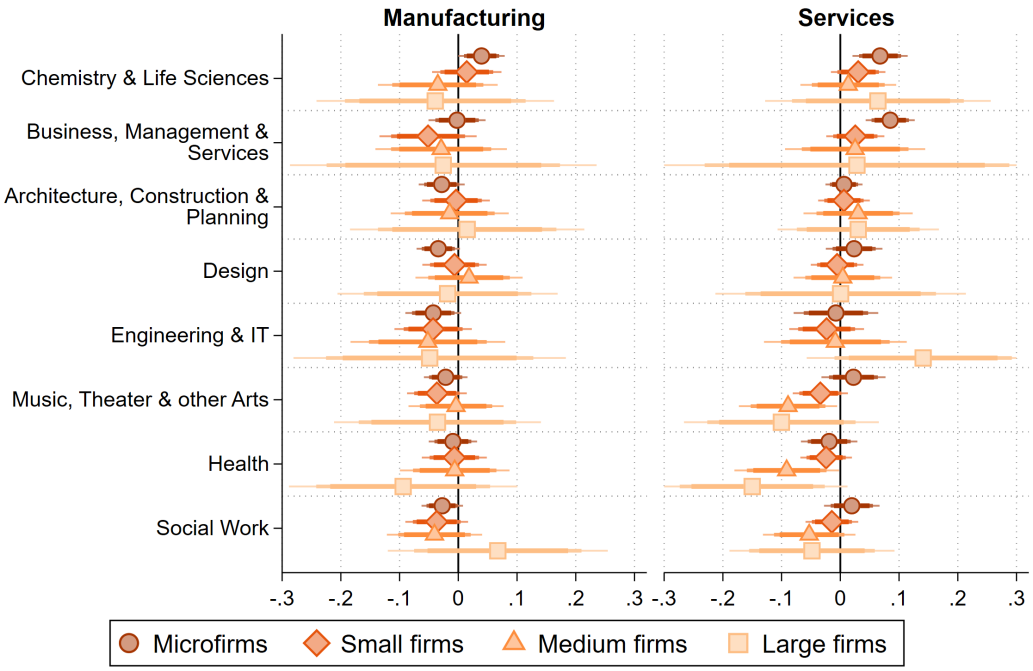
To further analyze which firms co-locate with UASs specializing in a particular field, we analyze the impact of the establishment of UASs on the number of firms in different size classes. The firm size also reveals whether the effect is due to existing bigger firms that co-locate with UASs or whether small firms, potentially start-ups, drive the effects on firm location. Firm size is defined by the number of employees in our dataset that comes from the SFSO (2019): microfirms (1-9 employees), small firms (10-49 employees), medium firms (50-249 employees), and large firms (250+ employees).

For our estimation, given small sub-sample sizes at the industry category level, particularly for large firms, we aggregate Bonaccorsi et al.'s (2017) eight industry categories into the manufacturing and service industries.[29] With this aggregated data, we re-estimate Equation (1) with the dependent variable being either the number of micro, small, medium, or large firms in either the manufacturing or service industries.

The results for firm size are depicted in Fig. 3. For UASs specializing in different fields, we find first that those specializing in Chemistry & Life Sciences are associated with a positive and significant effect on microfirms (potential start-ups) in both the manufacturing and service sectors. The positive effect on microfirms

[29] Manufacturing comprises science-based, supplier-dominated, scale-intensive, and specialized supplier manufacturing. Services comprises knowledge-intensive, supplier-dominated, physical network, and information network services.

in service industries is in line with that of UASs specializing in Chemistry & Life Sciences on knowledge-intensive, supplier-dominated and information network services—industries characterized mainly by microfirms. Knowledge-intensive and supplier-dominated services are also the two industry categories with the largest numbers of start-ups (see Table 1). The positive effect on microfirms in manufacturing industries reveals that the overall marginally significant effect of UASs specializing in Chemistry & Life Sciences on manufacturing industries (see Table 18 in Appendix D) is also likely to be driven by start-ups.



Notes: Fig. 3 shows the treatment effect of separate regressions of Equation (1) by firm size and by manufacturing and service industries. microfirms, 1-9 employees; small firms, 10-49 employees; medium firms, 50-249 employees; large firms, 250+ employees. All regressions include municipality and year fixed effects, control for population density, land use, the strength of regional infrastructure, and nearby UASs specializing in other fields. Depicted are 90%, 95%, and 99% confidence intervals.

Figure 3. Effects of UASs on firms by size in manufacturing and service industries

Second, UASs specializing in Business, Management & Services are associated with firm location in microfirms in the service industries. This finding also supports the results of our main analysis and indicates that the positive effects of those UASs on supplier-dominated, physical network, and information network services are likely driven by start-ups.

Third, among the UASs with a strong focus on engineering, those specializing in Architecture, Construction & Planning and Design have hardly any effect on firm location in different size classes in either manufacturing or service industries. The only negative effect on microfirms in manufacturing industries associated with UASs specializing in Design indicates that the negative effect (in the main analysis) on specialized supplier manufacturing is driven by a detrimental effect on the smallest firms. For UASs specializing in Engineering & IT, the tendency in manufacturing industries towards fewer firms across all firm sizes supports the argument in the main analysis that these UASs are particular drivers of the tertiarization of the Swiss economy. Moreover, the marginally positive effect of these UASs on large service industry firms reveals that the negative effect on knowledge-intensive business services (found in the main analysis) is associated with a consolidation process. In other words, the knowledge outputs of these UASs are beneficial for few large firms, at the expense of the smaller ones.

Fourth, Fig. 3 reveals that the negative albeit insignificant effects (in the main analysis) on firm location in service industries associated with UASs specializing in Health result from a decrease in the number of large firms. Yet given that growth in the number of large firms is very modest, one should be cautious about overestimating the economic impact of these negative effects. Overall, this further analysis confirms the finding of the main analysis that positive effects on firm

location are driven predominantly by UASs specializing in the fields of Chemistry & Life Sciences and Business, Management & Services. The positive effects on firm location associated with UASs specializing in these two fields are—according to this further analysis—initiated by microfirms, which are likely start-ups. The absence of widespread effects on medium or large firms also indicates that the positive effects on firm location are not mere artifacts of existing firms relocating from the control to the treatment group.

6.4. Robustness Checks

To provide evidence against potential reverse causality concerns, i.e., the problem that UASs were established mainly in regions with strong regional firm location, we run an additional robustness check by exchanging our dependent and independent variables. We thus run a regression where the dummy for a UAS being established in a particular field k (UAS_{it}^{k}) is the dependent variable and regional firm location in a municipality i at time t and in industry category m is the independent variable. The corresponding regression equation looks as follows:

$$\begin{aligned}\text{UAS}_{it}^{k} =& \alpha + \beta \text{firm location}_{it}^{m} \\ &+ \boldsymbol{x}'_{i(t-1)}\boldsymbol{\rho} + \tau_t + \phi_i + \mu_{it}.\end{aligned} \tag{2}$$

The setting as described in Equation (2) allows us to estimate whether changes in the probability of being nearby a newly established UAS could be driven by a municipality's regional firm location in a particular industry. This estimated coefficient is represented by β in Equation (2).

Estimated coefficients close to zero would support our argument that our results are not a mere artifact of reverse causality because being nearby a newly established UAS would not be explained by the regional firm location in a municipality and in a particular industry. Such a finding would imply that the positive effects on regional firm location that we find in our main analysis would then be driven by the establishment of UASs and not the other way around.

Table 20 in Appendix E indeed shows estimated coefficients that are very close to zero. Therefore, the regional firm location in a particular industry does not predict the establishment of a UAS in a particular field of study. In contrast, positive effects on regional firm location in a particular industry are rather driven by newly established UASs specializing in a particular field of study.

7. Conclusions and Implications

This paper investigates heterogeneities in the effects of HEIs in different fields on firm location, i.e., the number of either start-ups or firms that locate in a region, in different industries. Drawing on the literature on knowledge spillovers, we argue that heterogeneities in the effects of HEIs on firm location are likely to appear, because the two main knowledge outputs that HEIs produce—new knowledge and human capital—differ across the fields in which the HEIs specialize. Depending on the field, the new knowledge created is more or less codified or has a more applied or basic orientation, and the human capital from HEIs in different fields varies with respect to its specificity.

These differences in knowledge outputs produced across fields are mirrored by differences in the knowledge inputs needed by firms in particular industries. De-

pending on the industry, firms draw knowledge from different sources such as HEIs, customers, or suppliers, and become involved in different innovation patterns that require particular types of knowledge, e.g., radical or incremental product or process innovations. Furthermore, firms have industry-specific requirements for the human capital that HEIs produce. In sum, the effects of HEIs on firm location are likely to be heterogeneous, depending on the particular field-industry combination. Therefore, answering the question of which field-industry combination leads to positive effects on firm location calls for empirical analysis.

We answer this question by exploiting the establishment of UASs—bachelor degree-granting HEIs in Switzerland that teach and conduct applied research—in fields as diverse as Chemistry & Life Sciences, Design, Business, Management & Services, and Social Work. We combine this information on the establishment of UASs specializing in particular fields with data on firms in different industries. We use a taxonomy of manufacturing and service industries suggested by Bonaccorsi et al. (2013) to construct eight industry categories that represent groups of firms with different knowledge needs and innovation patterns.

Our main analysis reveals four broad patterns. First, UASs specializing in Chemistry & Life Sciences are associated with positive effects on firm location across knowledge-intensive, supplier-dominated, and information network services, whereas they have no effect on manufacturing industries. Second, UASs specializing in Business, Management & Services are associated with increases in firm location in all service industries except knowledge-intensive business services and with no effects on firms in the manufacturing industries. Third, for UASs specializing in fields with a strong focus on engineering (Architecture, Construction & Planning, Design, and Engineering & IT), we find only significant positive effects

on firm location in supplier-dominated and physical network services. Indeed, UASs specializing in Engineering & IT are even detrimental to firm location in some manufacturing industries. Fourth, UASs specializing in fields linked mostly to the humanities (Music, Theater & other Arts, Health and Social Work) have positive effects on supplier-dominated services but—surprisingly—potentially negative effects on firm location in the manufacturing industries.

In a further analysis, we investigate which firm sizes drive the effects across manufacturing and service sectors. Our findings show that the positive effects on firm location—associated mainly with UASs specializing in the fields of Chemistry & Life Sciences and Business, Management & Services—are driven by microfirms, i.e., start-ups. Moreover, we find UASs specializing in Engineering & IT positively affect the firm location of large firms in the service industries (with the number of medium firms tending to decrease), suggesting that these UASs contribute to an increase in the consolidation in the service industries. A second effect, linked mainly to these same UASs, is their apparent promotion of the tertiarization of the Swiss economy, i.e., the trend toward a more service-oriented economy, because they facilitate the transition from manufacturing to service jobs.

From a policy evaluation perspective, we find that the establishment of UASs in Switzerland fosters firm location and stimulates the ongoing tertiarization of the Swiss economy. Nonetheless, three qualifications apply: First, firm location overall is affected by UASs specializing in only two of the eight fields: Chemistry & Life Sciences and Business, Management & Services. Second, the results for Engineering & IT show that nearby UASs—depending on both their field and the industries of the firms that co-locate—can also initiate firm consolidation within an industry. Third, as the average growth rates in the number of firms are generally

modest, the additional effects on firm location associated with the establishment of UASs tend to be economically moderate.

As for the more general discussion on the impacts of HEIs that teach and conduct applied research, our analysis on heterogeneities across industries reveals an important finding: UASs—when they have a positive effect—predominantly affect industries characterized by process innovations. In contrast, the literature on knowledge spillovers, dominated by analyses of academic universities, tends to focus predominantly on positive effects of universities radical innovations.

Taken together, our findings yield two important implications for policy makers who are responsible for designing an higher education system that supports or improves a regional innovation ecosystem. First, effective policies must focus on a regional match between the knowledge output of the local HEI and the knowledge inputs required by the local firms. The knowledge of applied HEI in general appears to match particularly well with small firms in service industries that focus radical service innovations but even more so on incremental product or process innovations. Such regions—presumably often located outside of major innovation centers—might profit particularly from the establishment of an applied HEI.

Second, the pattern of impacts of UASs, with their focus on applied research, on regional firm location across industries differs from the patterns found in earlier studies focusing on academic universities. Industries with an increase in regional firm location associated with a UAS are often characterized by incremental process or product innovations, and in some cases by radical service innovations. In contrast, academic universities, with their basic research, foster firm location particularly in industries with radical product innovations. These different patterns imply that the two types of HEI could act as complements within a regional in-

novation ecosystem. Therefore, complementing academic universities with HEIs focusing on applied research—thereby enlarging the overall match between knowledge outputs and required knowledge inputs—would likely considerably strengthen a regional innovation ecosystem.

Our study has at least four limitations. The first limitation is that the fields of study and the industry categories we use in our analysis are still relatively broad. We relied on Bonaccorsi et al.'s (2013) taxonomy—inter alia—to get comparable results with earlier studies. Yet, aggregating fields of study and industries into larger groups always comes at the cost of missing some heterogeneity across more fine-grained categories. The second limitation is that using a binary identifier for the presence of an applied HEI neglects the importance of the size of an HEI. This size, however, most likely changes over time. Thus, learning more about the growth effects of existing HEI would be important for policy decisions on allocating resources within an HEI system. Still, our data do not allow for such analyses.

The third limitation is that our setting does not allow us to distinguish between the effects of the two main outputs of HEI (i.e., human capital and R&D). Therefore, we cannot answer whether applied HEI should focus more strongly on teaching, research, or both. The fourth limitation is that we cannot directly analyze the effects of interactions between different types of HEIs, e.g., the interactions between the co-location of UASs and academic universities within the same region. This limitation arises from a lack of variation in the exposure to academic universities (with basic research) during our period of analysis because these HEIs were established decades earlier than the first UASs. However, an empirical examination of the theoretically predicted positive interaction effects between basic and applied research institutions (e.g., Leyden and Menter 2018,0) would

yield valuable information for regional policies aimed at designing HEI systems that meet the knowledge needs of industries by exploiting interactions between different types of HEIs.

These limitations and the importance of focusing more strongly on effect heterogeneity put the need for fine-grained and large-scale datasets at the center of future avenues of research. A beneficial source of fine-grained and large-scale data is "text-as-data." Exploiting, for example, curricula of study courses, job ads of firms, or patents and annual reports of HEIs, allow future researchers to more precisely categorize fields of study, industries of firms, or types and sizes of HEI in a fine-grained, data-driven way. Using such fine-grained categories provides a pathway to study effect heterogeneity in more detail, thereby reaching closer to the (causal) underlying mechanisms of the effects of HEIs on the regional economy. These empirical findings would provide vital information for policy makers to establish and design HEI systems that are able to meet the needs of the local industry, to further improve the regional innovation ecosystem, and to ultimately foster regional firm location.

Appendix A Study Programs and Fields of Study

Table 3: Study programs and their respective field of study (not exhaustive)

Bachelor Degree Programs by Fields of Study	
Chemistry & Life Sciences	
Biotechnology	Life Sciences Technologies
Chemistry	Molecular Life Sciences
Environmental Engineering	Oenology
Food Technology	
Business, Management & Services	
Banking & Finance	Hospitality Management
Business Administration	Information Science
Business Information Technology	International Business Administration
Business Law	International Business Management
Communication	Leisure Management
Service Design	Sport Management
Digital Business Management	Tourism
Facility Management	
Architecture, Construction & Planing	
Architecture	Geomatics
Civil Engineering	Landscape Architecture
Construction Management	Spatial Planning
Digital Construction	Surveying & Mapping
Design	
Conservation	Product & Industrial Design
Fashion Design	Textile Design
Illustration	Visual Communication
Interior Design	

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Bachelor Degree Programs by Fields of Study	
Engineering & IT	
Artificial Intelligence & Machine Learning	Mechatronics
Automotive Engineering	Media Engineering
Aviation	Medical Informatics
Computer Engineering	Medical Technology
Computer Science	Microeletronics
Cyber Security	Microengineering
Data Science	Mobile Robotics
Digital Engineering	Optometry
Electrical Engineering	Photonics
Electronics	Process & Plant Engineering
Energy & Building Technology	Systems Engineering
Engineering & Management	Telecommunications
Industrial Design Engineering	Therminal Engineering
Mechanical Engineering	Transportation Systems
Music, Theater & other Arts	
Art & Design Communication	Literary Writing
Art & Education	Multimedia Production
Cinema	Music
Classical Music, Theory & Composition	Music & Movement
Conducting	Photography
Contemporary Dance	Theater
Fine Arts	Visual Arts
Interpretation & Performance	
Health	
Dental Hygiene	Nutrition & Dietetics
Health Promotion & Prevention	Occupational Therapy
Medical Radiology	Osteopathie
Midwifery	Physiotherapy
Nursing	
Social Work	
Social Work	

Notes: The list of study programs is not exhaustive. As our analysis focuses on bachelor's degree programs, other degree programs are not listed here. The assignment of study programs to UASs' fields of study is based on EAER (2014) where possible and otherwise assigned manually. Besides, there exist study programs in the fields of Agriculture & Forestry, Applied Psychology, Applied Linguistics and Sports. UASs in these fields are excluded from our analysis either due to missing outcome data or due to too small numbers of observations.

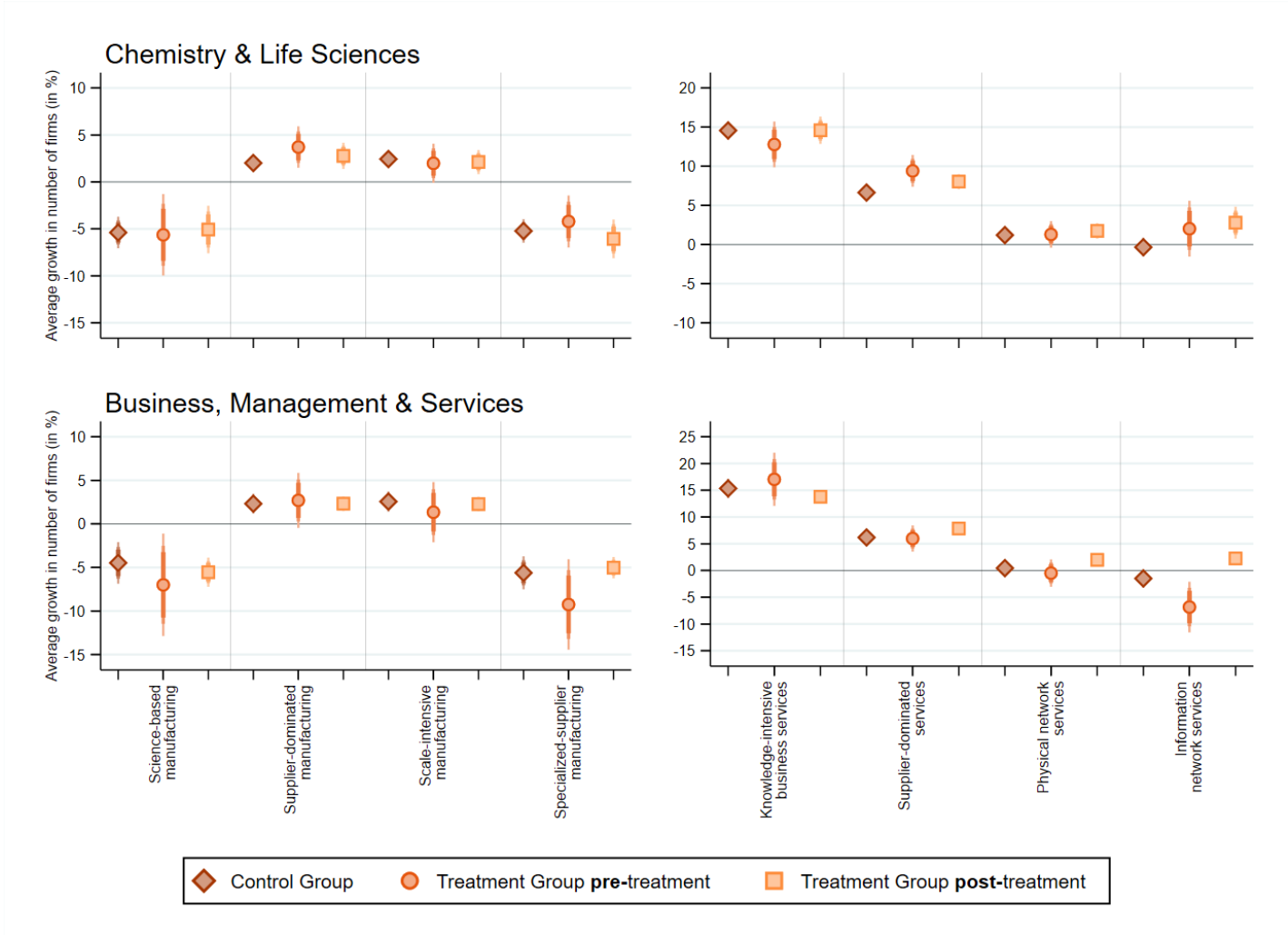

Figure 4. Average growth rates in the number of firms for UASs specializing in Chemistry & Life Sciences and Business, Management & Services

Notes: The figure shows the average growth rates in the number of firms (y-axis), separately for each of the eight industry categories (x-axis), as well as for the control group (diamond symbols), the treatment group in the pre-treatment period (circle symbols), and the treatment group in the post-treatment period (square symbols). Treatment and control groups correspond to UASs in Chemistry & Life Sciences in the two upper figures and to UASs in Business, Management & Services in the two lower figures. Vertical lines indicate confidence intervals at 90%, 95%, and 99%, respectively.

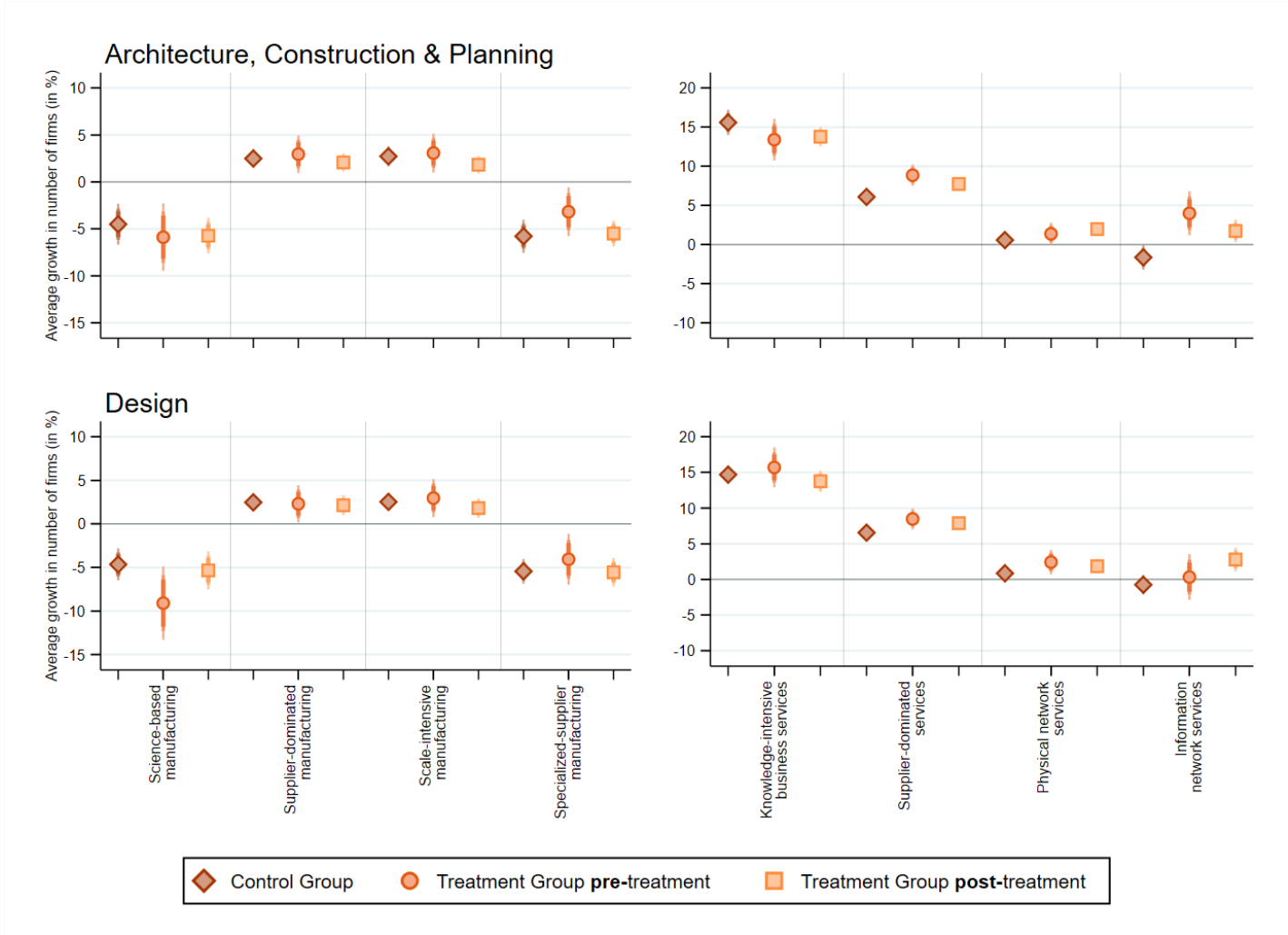

Figure 5. Average growth rates in the number of firms for UASs specializing in Architecture, Construction & Planning and Design

Notes: The figure shows the average growth rates in the number of firms (y-axis), separately for each of the eight industry categories (x-axis), as well as for the control group (diamond symbols), the treatment group in the pre-treatment period (circle symbols), and the treatment group in the post-treatment period (square symbols). Treatment and control groups correspond to UASs in Architecture, Construction & Planning in the two upper figures and to UASs Design in the two lower figures. Vertical lines indicate confidence intervals at 90%, 95%, and 99%, respectively.

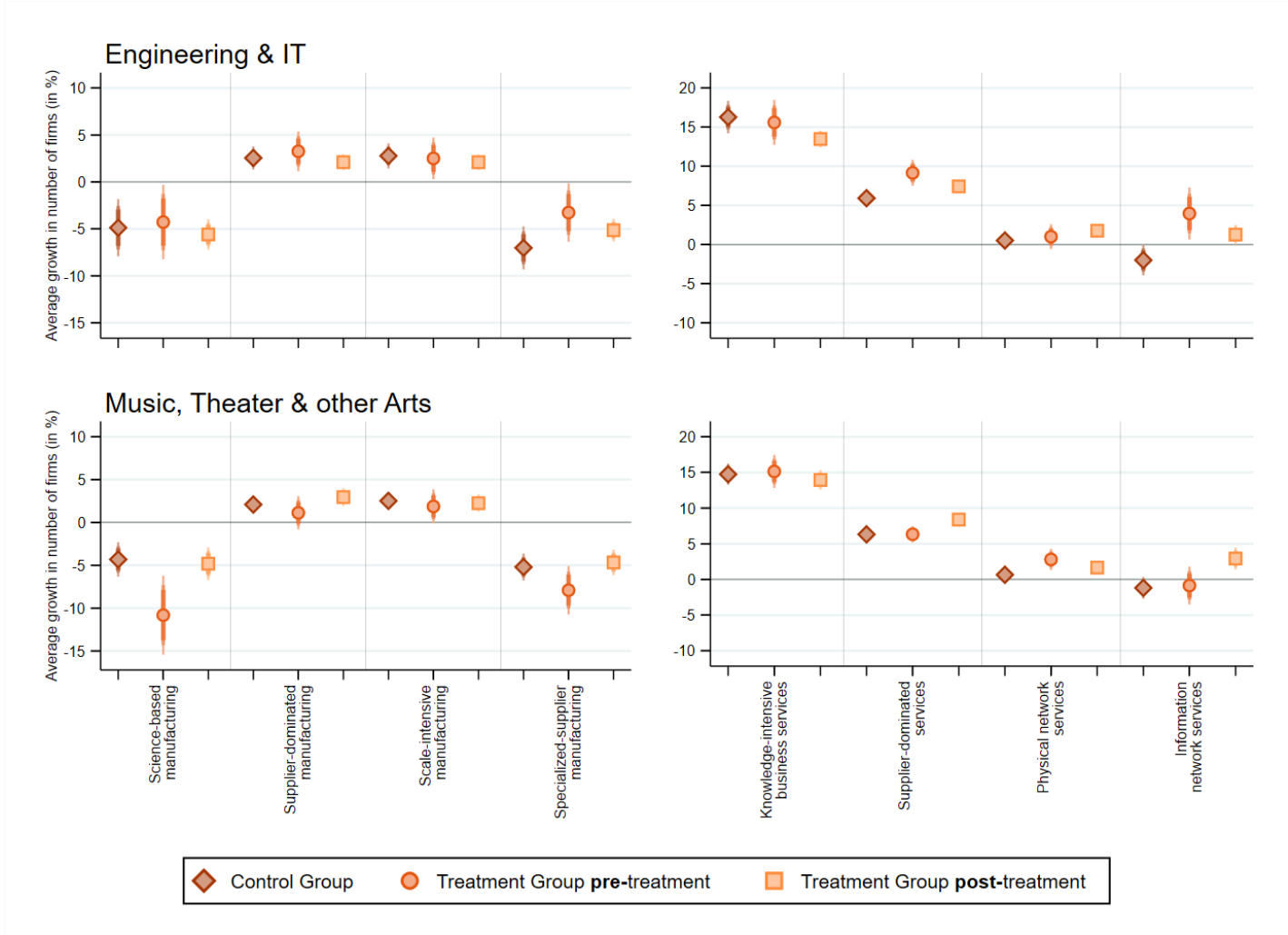

Figure 6. Average growth rates in the number of firms for UASs specializing in Engineering &IT and Music, Theater & other Arts

Notes: The figure shows the average growth rates in the number of firms (y-axis), separately for each of the eight industry categories (x-axis), as well as for the control group (diamond symbols), the treatment group in the pre-treatment period (circle symbols), and the treatment group in the post-treatment period (square symbols). Treatment and control groups correspond to UASs in Engineering & IT in the two upper figures and to UASs in Music, Theater & other Arts in the two lower figures. Vertical lines indicate confidence intervals at 90%, 95%, and 99%, respectively.

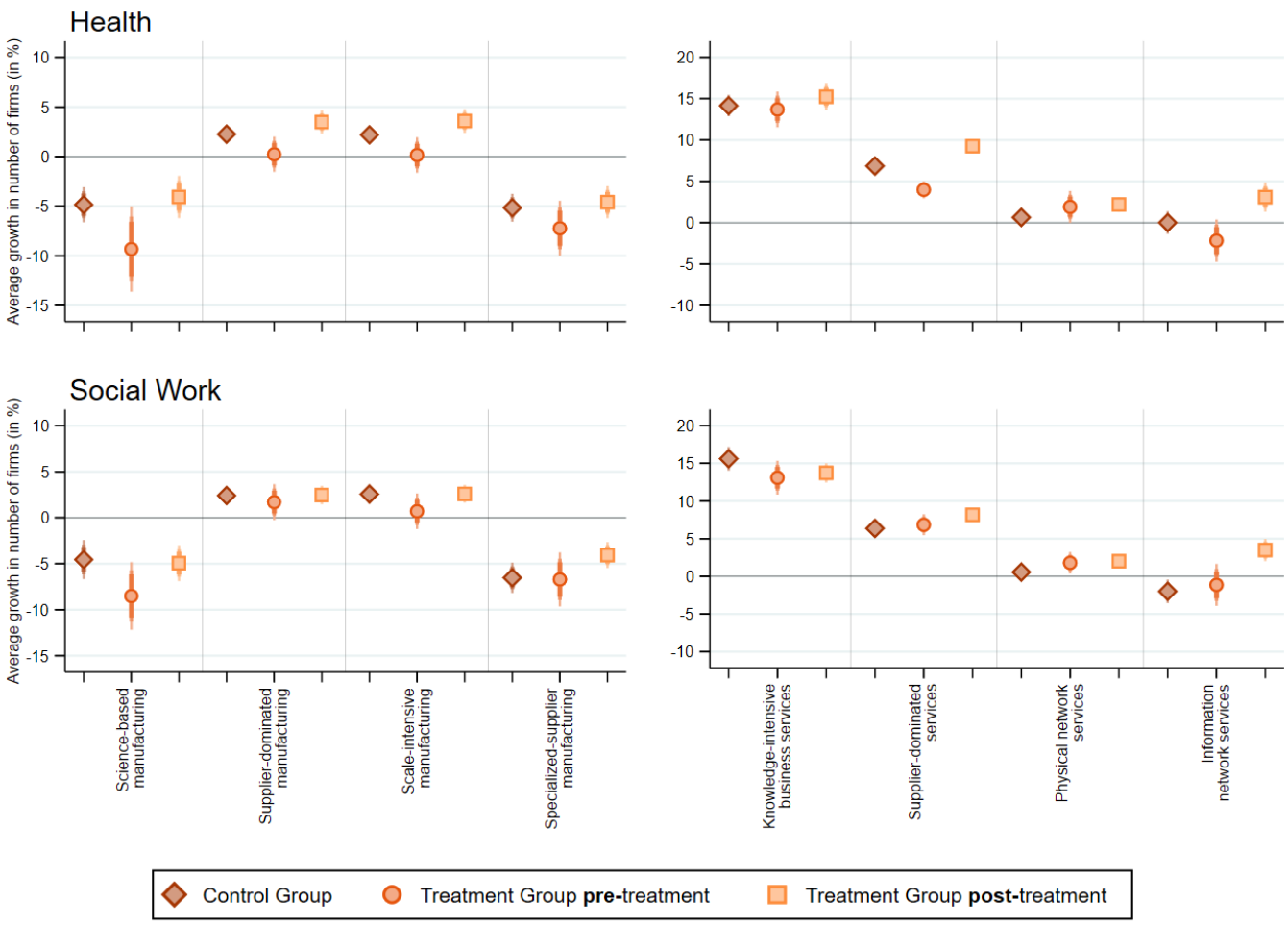

Figure 7. Average growth rates in the number of firms for UASs specializing in Health and Social Work

Notes: The figure shows the average growth rates in the number of firms (y-axis), separately for each of the eight industry categories (x-axis), as well as for the control group (diamond symbols), the treatment group in the pre-treatment period (circle symbols), and the treatment group in the post-treatment period (square symbols). Treatment and control groups correspond to UASs in Health in the two upper figures and to UASs in Social Work in the two lower figures. Vertical lines indicate confidence intervals at 90%, 95%, and 99%, respectively.

Appendix B Descriptive Statistics

Table 4: Firms by industry categories, year and treatment and control groups

	Treatment Group					Control Group					t-test
Year	*N*	Mean	*SD*	Min.	Max.	*N*	Mean	*SD*	Min.	Max.	
Total Number of Firms											
1995	1,826	157	762	0	23,899	396	102	180	0	1,673	***
1998	1,826	160	762	0	23,845	396	103	182	0	1,694	***
2001	1,826	163	777	0	24,516	396	102	185	0	1,701	***
2005	1,826	158	750	0	23,529	396	99	183	0	1,679	***
2008	1,826	165	784	0	24,616	396	100	187	0	1,701	***
2011	1,826	222	1,070	0	33,828	396	131	243	0	2,272	***
2012	1,826	224	1,091	0	34,845	396	133	249	0	2,300	***
2013	1,826	228	1,116	0	35,778	396	135	254	0	2,323	***
2014	1,826	236	1,154	0	37,082	396	139	262	0	2,362	***
2015	1,826	238	1,170	0	37,644	396	140	263	0	2,404	***
2016	1,826	240	1,178	0	37,936	396	142	266	0	2,448	***
2017	1,826	243	1,190	0	38,260	396	143	267	1	2,473	***
Science-based Manufacturing											
1995	1,826	1.43	6.05	0	163	396	0.65	2.15	0	23	***
1998	1,826	1.09	4.47	0	121	396	0.57	2.03	0	21	***
2001	1,826	1.25	4.83	0	126	396	0.62	2.15	0	22	***
2005	1,826	1.19	4.55	0	126	396	0.66	2.08	0	21	***
2008	1,826	1.28	5.52	0	154	396	0.71	2.42	0	25	***
2011	1,826	1.22	5.58	0	166	396	0.68	2.23	0	21	***
2012	1,826	1.21	5.37	0	161	396	0.69	2.19	0	20	***
2013	1,826	1.19	5.36	0	165	396	0.68	2.19	0	21	***
2014	1,826	1.17	5.31	0	166	396	0.66	2.11	0	22	***
2015	1,826	1.13	5.18	0	160	396	0.66	2.09	0	23	***
2016	1,826	1.08	4.76	0	144	396	0.62	2.01	0	21	***
2017	1,826	1.09	4.85	0	141	396	0.61	1.93	0	20	***
Supplier-dominated Manufacturing											
1995	1,826	8.55	34.84	0	1,118	396	6.39	9.56	0	90	**
1998	1,826	8.17	32.31	0	1,021	396	6.14	8.89	0	75	**
2001	1,826	7.86	30.27	0	942	396	5.80	8.23	0	63	**
2005	1,826	7.09	25.84	0	786	396	5.53	7.86	0	60	**
2008	1,826	7.07	25.49	0	787	396	5.39	7.65	0	57	**
2011	1,826	8.39	28.57	0	846	396	6.52	8.90	0	68	**
2012	1,826	8.26	28.09	0	849	396	6.48	8.91	0	69	**
2013	1,826	8.18	27.79	0	835	396	6.41	8.72	0	70	**
2014	1,826	8.31	27.86	0	829	396	6.53	8.86	0	73	**
2015	1,826	8.23	27.57	0	822	396	6.53	8.97	0	73	**
2016	1,826	8.11	26.91	0	789	396	6.50	9.01	0	66	**
2017	1,826	8.02	26.86	0	788	396	6.29	8.59	0	63	**

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	Treatment Group					Control Group					t-test
Year	*N*	Mean	*SD*	Min.	Max.	*N*	Mean	*SD*	Min.	Max.	
Scale-intensive Manufacturing											
1995	1,826	7.16	15.18	0	390	396	4.66	7.22	0	51	***
1998	1,826	7.02	14.12	0	333	396	4.66	7.20	0	57	***
2001	1,826	7.01	13.69	0	310	396	4.81	7.50	0	60	***
2005	1,826	6.49	12.23	0	258	396	4.55	7.06	0	52	***
2008	1,826	6.46	11.83	0	243	396	4.59	6.94	0	51	***
2011	1,826	7.29	13.16	0	260	396	5.47	8.04	0	55	***
2012	1,826	7.19	13.03	0	267	396	5.44	7.93	0	53	***
2013	1,826	7.16	12.86	0	257	396	5.58	8.04	0	55	***
2014	1,826	7.27	13.14	0	270	396	5.65	8.07	0	58	***
2015	1,826	7.25	13.20	0	273	396	5.62	7.95	0	58	***
2016	1,826	7.18	12.90	0	267	396	5.70	8.09	0	59	***
2017	1,826	7.18	13.18	0	289	396	5.74	7.97	0	58	***
Specialized-supplier Manufacturing											
1995	1,826	2.34	5.94	0	150	396	1.18	2.53	0	21	***
1998	1,826	1.86	4.38	0	97	396	1.00	2.16	0	20	***
2001	1,826	1.83	4.08	0	84	396	1.07	2.28	0	19	***
2005	1,826	1.80	3.86	0	71	396	1.02	2.23	0	19	***
2008	1,826	1.78	3.82	0	70	396	1.07	2.36	0	22	***
2011	1,826	1.72	3.62	0	64	396	1.07	2.33	0	20	***
2012	1,826	1.70	3.54	0	64	396	1.08	2.30	0	17	***
2013	1,826	1.65	3.45	0	59	396	1.07	2.31	0	19	***
2014	1,826	1.63	3.46	0	61	396	1.06	2.25	0	16	***
2015	1,826	1.57	3.38	0	59	396	1.03	2.21	0	17	***
2016	1,826	1.52	3.34	0	65	396	1.00	2.17	0	17	***
2017	1,826	1.47	3.37	0	75	396	0.90	2.01	0	16	***
Knowledge-intensive Business Services											
1995	1,826	26.69	169	0	5,869	396	10.72	25.30	0	264	***
1998	1,826	28.85	177	0	6,105	396	11.67	27.83	0	304	***
2001	1,826	33.37	203	0	7,029	396	13.05	31.32	0	335	***
2005	1,826	32.08	199	0	6,906	396	12.48	30.28	0	298	***
2008	1,826	34.57	216	0	7,481	396	13.42	32.24	0	306	***
2011	1,826	56.17	351	0	12,137	396	23.54	52.12	0	514	***
2012	1,826	57.31	364	0	12,734	396	24.09	54.30	0	511	***
2013	1,826	58.72	377	0	13,213	396	24.78	56.00	0	507	***
2014	1,826	61.83	397	0	13,905	396	26.36	59.06	0	534	***
2015	1,826	62.69	406	0	14,204	396	26.63	59.38	0	540	***
2016	1,826	63.58	412	0	14,456	396	27.26	60.74	0	543	***
2017	1,826	64.65	419	0	14,695	396	27.83	61.77	0	552	***

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	Treatment Group					Control Group					t-test
Year	*N*	Mean	*SD*	Min.	Max.	*N*	Mean	*SD*	Min.	Max.	
Supplier-dominated Services											
1995	1,826	78.10	407	0	12,101	396	56.52	104	0	945	**
1998	1,826	79.19	403	0	11,959	396	56.88	105	0	954	**
2001	1,826	78.46	394	0	11,720	396	55.80	105	0	973	**
2005	1,826	76.66	381	0	11,278	396	53.50	103	0	951	**
2008	1,826	78.98	391	0	11,569	396	53.47	104	0	962	**
2011	1,826	110	512	0	15,278	396	73.61	138	0	1,269	***
2012	1,826	112	522	0	15,681	396	74.65	141	0	1,356	***
2013	1,826	113	532	0	16,041	396	75.47	143	0	1,360	***
2014	1,826	118	548	0	16,614	396	77.62	147	0	1,386	***
2015	1,826	119	555	0	16,867	396	77.96	147	0	1,406	***
2016	1,826	121	560	0	16,976	396	79.27	150	0	1,445	***
2017	1,826	123	565	0	17,043	396	80.21	151	0	1,472	***
Physical-network Services											
1995	1,826	25.76	91.48	0	2,809	396	17.56	28.17	0	256	***
1998	1,826	26.71	89.72	0	2,671	396	17.61	28.18	0	239	***
2001	1,826	25.43	82.82	0	2,413	396	16.94	27.28	0	243	***
2005	1,826	25.42	79.25	0	2,249	396	16.83	28.49	0	276	***
2008	1,826	26.47	80.28	0	2,161	396	17.71	29.35	0	264	***
2011	1,826	26.66	92.94	0	2,550	396	16.46	29.89	0	301	***
2012	1,826	26.77	92.75	0	2,527	396	16.70	30.95	0	326	***
2013	1,826	26.91	93.47	0	2,562	396	16.84	32.12	0	360	***
2014	1,826	27.18	93.88	0	2,554	396	17.25	33.14	0	385	***
2015	1,826	27.17	94.26	0	2,557	396	17.35	33.85	0	403	***
2016	1,826	26.89	91.78	0	2,482	396	17.44	33.36	0	388	***
2017	1,826	26.61	90.07	0	2,385	396	17.29	32.75	0	379	***
Information-network Services											
1995	1,826	6.84	42.90	0	1,370	396	4.43	9.07	0	95	**
1998	1,826	6.90	49.11	0	1,609	396	3.99	8.49	0	80	**
2001	1,826	7.57	58.04	0	1,962	396	4.07	9.40	0	93	**
2005	1,826	7.67	58.31	0	1,938	396	4.00	9.87	0	99	**
2008	1,826	8.15	67.18	0	2,246	396	3.95	9.95	0	99	**
2011	1,826	9.95	85.01	0	2,632	396	3.87	11.57	0	130	***
2012	1,826	10.13	85.65	0	2,665	396	4.00	11.80	0	133	***
2013	1,826	10.33	87.42	0	2,757	396	4.13	12.02	0	133	***
2014	1,826	10.67	88.47	0	2,795	396	4.28	12.31	0	137	***
2015	1,826	10.69	88.14	0	2,806	396	4.20	12.02	0	141	***
2016	1,826	10.80	88.99	0	2,848	396	4.25	11.80	0	128	***
2017	1,826	10.84	90.29	0	2,923	396	4.08	11.36	0	121	***

Notes: The assignment to treatment and control groups in the table is based on whether a municipality belongs to any treatment group (independent of the field of the UAS). For number of municipalities in treatment and control groups by field, see Table 6. Significance Level: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Industry categories and number of firms in each sub-industry (in 2008)

NOGA	Industry Description	Treatment Group	Control Group
C 21	Manufacture of basic pharmaceutical products & pharmaceutical preparations	201	33
C 26	Manufacture of computer, electronic & optical products	2,136	249
	Total science-based manufacturing	2,337	282
C 13	Manufacture of textiles	588	94
C 14	Manufacture of wearing apparel	750	66
C 15	Manufacture of leather & related products	176	32
C 16	Manufacture of wood & of products of wood & cork, except furniture & manufacture of articles of straw & plaiting materials	5,161	1,232
C 17	Manufacture of paper & paper products	195	19
C 18	Printing & reproduction of recorded media	2,435	238
C 31	Manufacture of furniture	873	143
C 32	Other manufacturing	2,735	312
	Total supplier-dominated manufacturing	12,913	2,136
C 10	Manufacture of food products	1,720	421
C 11	Manufacture of beverages	344	55
C 12	Manufacture of tobacco products	13	1
C 19	Manufacture of coke & refined petroleum products	14	1
C 20	Manufacture of chemicals & chemical products	619	60
C 22	Manufacture of rubber & plastic products	713	96
C 23	Manufacture of other non-metallic mineral products	1,182	213
C 24	Manufacture of basic metals	249	37
C 25	Manufacture of fabricated metal products, except machinery & equipment	6,568	870
C 29	Manufacture of motor vehicles, trailers & semi-trailers	188	20
C 30	Manufacture of other transport equipment	187	42
	Total scale-intensive manufacturing	11,797	1,816
C 27	Manufacture of electrical equipment	802	103
C 28	Manufacture of machinery & equipment n.e.c.	2,266	277
C 33	Repair & installation of machinery & equipment	1,812	302
	Total specialized suppliers manufacturing	4,880	682
J 62	Computer programming, consultancy & related activities	10,439	634
J 63	Information service activities	551	46
M 69	Legal & accounting activities	11,835	1,078
M 70	Activities of head offices & management consultancy activities	10,730	647
M 71	Architectural & engineering activities & technical testing & analysis	17,115	1,989
M 72	Scientific research & development	698	59
M 73	Advertising & market research	3,425	223
M 74	Other professional, scientific & technical activities	6,071	415
R 90	Creative, arts & entertainment activities	1,581	147
R 91	Libraries, archives, museums & other cultural activities	684	78
	Total knowledge-intensive business services	63,129	5,316

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NOGA	Industry Description	Treatment Group	Control Group
G 47	Retail trade, except of motor vehicles & motorcycles	42,495	6,354
I 55	Accommodation	3,165	2,096
I 56	Food & beverage service activities	19,920	3,443
L 68	Real estate activities	4,780	477
M 75	Veterinary activities	760	127
N 77	Rental & leasing activities	871	66
N 78	Employment activities	2,320	103
N 79	Travel agency, tour operator reservation service & related activities	2,064	344
N 80	Security & investigation activities	546	59
N 81	Services to buildings & landscape activities	6,823	881
N 82	Office administrative, office support & other business support activities	1,909	142
P 85	Education	13,695	1,893
Q 86	Human health activities	15,845	1,704
Q 87	Residential care activities	2,923	457
Q 88	Social work activities without accommodation	4,322	368
R 92	Gambling & betting activities	41	7
R 93	Sports activities & amusement & recreation activities	2,689	363
S 94	Activities of membership organisations	5,172	672
S 95	Repair of computers & personal & household goods	1,828	178
S 96	Other personal service activities	12,048	1,440
	Total supplier-dominated services	144,216	21,174
D 35	Electricity, gas, steam & air conditioning supply	534	180
E 36	Water collection, treatment & supply	192	36
E 37	Sewerage	471	105
E 38	Waste collection, treatment & disposal activities & materials recovery	614	85
E 39	Remediation activities & other waste management services	17	3
G 45	Wholesale & retail trade & repair of motor vehicles & motorcycles	12,537	1,898
G 46	Wholesale trade, except of motor vehicles & motorcycles	19,985	1,965
H 49	Land transport & transport via pipelines	6,865	1,315
H 50	Water transport	122	11
H 51	Air transport	172	22
H 52	Warehousing & support activities for transportation	1,665	293
H 53	Postal & courier activities	5,154	1,098
	Total physical network services	48,328	7,011
J 58	Publishing activities	1,200	127
J 59	Motion picture, video & television program production, sound recording & music publishing activities	1,382	71
J 60	Programming & broadcasting activities	117	15
J 61	Telecommunications	798	66
K 64	Financial service activities, except insurance & pension funding	4,073	630
K 65	Insurance, reinsurance & pension funding, except compulsory social security	1,645	268
K 66	Activities auxiliary to financial services & insurance activities	5,672	387
	Total information network services	14,887	1,564

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NOGA	Industry Description	Treatment Group	Control Group
B 05	Mining of coal & lignite	0	0
B 06	Extraction of crude petroleum & natural gas	0	0
B 07	Mining of metal ores	0	0
B 08	Other mining & quarrying	242	84
B 09	Mining support service activities	5	1
F 41	Construction of buildings	3,978	859
F 42	Civil engineering	883	185
F 43	Specialized construction activities	27,861	4,533
O 84	Public administration & defense & compulsory social security	6,672	1,394
	Total not-categorized industries	39,641	7,056
	Industries without data on the number of firms		
A 01	Crop & animal production, hunting & related service activities	N/D	N/D
A 02	Forestry & logging	N/D	N/D
A 03	Fishing & aquaculture	N/D	N/D
T 97	Activities of households as employers of domestic personnel	N/D	N/D
T 98	Undifferentiated goods- & services- producing activities of private households for own use	N/D	N/D
U 99	Activities of extraterritorial organizations & bodies	N/D	N/D

Notes: The table shows the number of firms in each of the 86 NOGA industries for the treatment and control groups exemplary for the year 2008. The NOGA is the Swiss general classification of economic activities that follows very closely the NACE, the statistical classification of economic activities in the European Community. We followed the taxonomy by Bonaccorsi et al. (2013) to assign the 80 NOGA industry divisions to 8 industry categories. The only adjustment we have to make is the industry "veterinary activities" (M 75) that is not classified in the standard taxonomy of Bonaccorsi et al. (2013). We assigned it to the total supplier-dominated services because this category also comprises human health activities. The three industry sections "mining & quarrying", "construction" and "public administration & defense; compulsory social security" are not included in the taxonomy. For the industry sections "agriculture, forestry & fishing", "activities of households as employers; undifferentiated goods- & services-producing activities of households for own use" and "activities of extraterritorial organizations & bodies" we have no data. These industry sectors are thus completely excluded from the analysis (as in Bonaccorsi et al. 2013).

Table 6: Observations by study field and industry used in the PPML estimation

		Manufacturing				Services			
	Full Sample	Science-based	Supplier-dominated	Scale-intensive	Specialized supplier	Knowledge-intensive	Supplier-dominated	Physical network	Information network
Observations per year	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
– Separated by FE	0	1071	104	112	685	24	1	20	251
= Non-separated observations	2,222	1,151	2,118	2,110	1,537	2,198	2,221	2,202	1,971
Non-separated observations by field and Treatment and Control Groups									
UASs in Chemistry & Life Sciences									
Treatment Group	725	411	707	701	526	720	725	717	660
Control Group	1,497	740	1,411	1,409	1,011	1,478	1,496	1,485	1,311
UASs in Business, Management & Services									
Treatment Group	1,499	825	1,430	1,428	1,090	1,483	1,498	1,482	1,336
Control Group	723	326	688	682	447	715	723	720	635
UASs in Architecture, Construction & Planning									
Treatment Group	1,329	747	1,278	1,276	979	1,321	1,329	1,315	1,182
Control Group	893	404	840	834	558	877	892	887	789
UASs in Design									
Treatment Group	979	563	942	936	731	977	979	973	890
Control Group	1,243	588	1,176	1,174	806	1,221	1,242	1,229	1,081
UASs in Engineering & IT									
Treatment Group	1,613	919	1,542	1,545	1,180	1,598	1,612	1,596	1,423
Control Group	609	232	576	565	357	600	609	606	548
UASs in Music, Theater & other Arts									
Treatment Group	1,213	686	1,168	1,162	888	1,207	1,213	1,203	1,096
Control Group	1,009	465	950	948	649	991	1,008	999	875
UASs in Health									
Treatment Group	1,065	565	1,021	1,007	751	1,050	1,064	1,050	959
Control Group	1,157	586	1,097	1,103	786	1,148	1,157	1,152	1,012
UASs in Social Work									
Treatment Group	1,241	725	1,194	1,192	941	1,230	1,241	1,229	1,119
Control Group	981	426	924	918	596	968	980	973	852
UASs in all fields									
Treatment Group	1,826	1,007	1,747	1,745	1,306	1,807	1,825	1,807	1,617
Control Group	396	144	371	365	231	391	396	395	354

Notes: Observations separated by FE are municipalities that show zero firms in the particular industry over the entire time period. These observations contain no relevant information and have to be dropped to solve maximum likelihood estimation (Correia et al., 2019b).

Table 7: Observations with zero values per industry and year

Year	Treatment Group		Control Group		Treatment Group		Control Group	
	Absolute	Share	Absolute	Share	Absolute	Share	Absolute	Share
	Science-based manufacturing				*Knowledge-intensive business services*			
1995	1125	61.61%	303	76.52%	225	12.32%	84	21.21%
1998	1224	67.03%	310	78.28%	200	10.95%	71	17.93%
2001	1189	65.12%	307	77.53%	174	9.53%	67	16.92%
2005	1194	65.39%	303	76.52%	189	10.35%	66	16.67%
2008	1192	65.28%	307	77.53%	167	9.15%	58	14.65%
2011	1204	65.94%	309	78.03%	59	3.23%	24	6.06%
2012	1205	65.99%	305	77.02%	66	3.61%	22	5.56%
2013	1216	66.59%	306	77.27%	66	3.61%	28	7.07%
2014	1225	67.09%	304	76.77%	59	3.23%	20	5.05%
2015	1241	67.96%	302	76.26%	58	3.18%	21	5.30%
2016	1242	68.02%	307	77.53%	57	3.12%	24	6.06%
2017	1250	68.46%	306	77.27%	50	2.74%	24	6.06%
	Supplier-dominated manufacturing				*Supplier-dominated services*			
1995	282	15.44%	59	14.90%	20	1.10%	4	1.01%
1998	279	15.28%	54	13.64%	23	1.26%	4	1.01%
2001	292	15.99%	60	15.15%	22	1.20%	4	1.01%
2005	301	16.48%	64	16.16%	27	1.48%	5	1.26%
2008	303	16.59%	70	17.68%	32	1.75%	9	2.27%
2011	240	13.14%	52	13.13%	12	0.66%	2	0.51%
2012	229	12.54%	55	13.89%	13	0.71%	4	1.01%
2013	245	13.42%	56	14.14%	11	0.60%	2	0.51%
2014	237	12.98%	48	12.12%	10	0.55%	1	0.25%
2015	240	13.14%	55	13.89%	12	0.66%	1	0.25%
2016	248	13.58%	54	13.64%	10	0.55%	2	0.51%
2017	245	13.42%	53	13.38%	9	0.49%	1	0.25%
	Scale-intensive manufacturing				*Physical networks services*			
1995	278	15.22%	93	23.48%	51	2.79%	3	0.76%
1998	298	16.32%	89	22.47%	64	3.50%	12	3.03%
2001	316	17.31%	87	21.97%	73	4.00%	12	3.03%
2005	343	18.78%	88	22.22%	117	6.41%	26	6.57%
2008	339	18.57%	83	20.96%	123	6.74%	26	6.57%
2011	261	14.29%	68	17.17%	104	5.70%	19	4.80%
2012	270	14.79%	65	16.41%	105	5.75%	24	6.06%
2013	294	16.10%	63	15.91%	103	5.64%	24	6.06%
2014	279	15.28%	62	15.66%	102	5.59%	24	6.06%
2015	269	14.73%	67	16.92%	106	5.81%	26	6.57%
2016	253	13.86%	65	16.41%	109	5.97%	28	7.07%
2017	257	14.07%	63	15.91%	107	5.86%	31	7.83%

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Year	Treatment Group		Control Group		Treatment Group		Control Group	
	Absolute	Share	Absolute	Share	Absolute	Share	Absolute	Share
	Specialized-supplier manufacturing				*Information networks services*			
1995	823	45.07%	235	59.34%	565	30.94%	91	22.98%
1998	926	50.71%	254	64.14%	588	32.20%	108	27.27%
2001	906	49.62%	254	64.14%	610	33.41%	115	29.04%
2005	917	50.22%	253	63.89%	643	35.21%	129	32.58%
2008	912	49.95%	246	62.12%	631	34.56%	128	32.32%
2011	918	50.27%	244	61.62%	620	33.95%	162	40.91%
2012	910	49.84%	242	61.11%	600	32.86%	157	39.65%
2013	931	50.99%	241	60.86%	591	32.37%	150	37.88%
2014	934	51.15%	245	61.87%	579	31.71%	146	36.87%
2015	945	51.75%	248	62.63%	576	31.54%	144	36.36%
2016	956	52.35%	253	63.89%	565	30.94%	144	36.36%
2017	979	53.61%	263	66.41%	571	31.27%	148	37.37%
	All Industries							
1995	8	0.44%	1	0.25%				
1998	7	0.38%	1	0.25%				
2001	8	0.44%	2	0.51%				
2005	8	0.44%	3	0.76%				
2008	10	0.55%	3	0.76%				
2011	5	0.27%	1	0.25%				
2012	6	0.33%	1	0.25%				
2013	6	0.33%	1	0.25%				
2014	6	0.33%	1	0.25%				
2015	7	0.38%	1	0.25%				
2016	6	0.33%	1	0.25%				
2017	4	0.22%	1	0.25%				

Notes: The table shows the share of municipalities in a year and industry category that report zero firms.

Table 8: UAS establishment years and treatment lags given by data structure

	Year of outcome variable											
Year of UAS establishment	1995	1998	2001	2005	2008	2011	2012	2013	2014	2015	2016	2017
1997	pre-treatment		4-year lag									
1998	pre-treatment		3-year lag									
1999	pre-treatment		2-year lag									
2000	no establishment in this year											
2001	pre-treatment			4-year lag								
2002	pre-treatment			3-year lag								
2003	pre-treatment			2-year lag								
2004	pre-treatment				4-year lag							
2005	pre-treatment				3-year lag							
2006	pre-treatment				2-year lag							
2007	pre-treatment					4-year lag						
2008	no establishment in this year											
2011	pre-treatment							2-year lag				
2012	no establishment in this year											
2013	no establishment in this year											
2014	pre-treatment										2-year lag	
2015	no establishment in this year											
2016	no post-treatment outcome available (due to treatment lag)											
2017	no establishment in this year											

Notes: The table shows how the lag structure we assume in our estimation strategy leads to different treatment lags, depending on the year in which a UAS was established. Pre-treatment years are depicted in light shading, post-treatment years in dark shading, the lag with which a UAS establishment is considered in our analysis thereby depends on the establishment year because we only have data on a three-year basis for earlier years.

Appendix C Detailed Results Main Analysis

Table 9: Regressions for firm location across industries on UASs in **Chemistry & Life Sciences** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based	0.2697	0.2975	0.0642	0.0651	0.0721*	0.0784*	0.0915**
manufacturing	(0.1698)	(0.1848)	(0.0430)	(0.0439)	(0.0430)	(0.0433)	(0.0440)
Log likelihood	-67,168.68	-67,064.054	-15,064.681	-15,064.671	-15,060.928	-15,060.234	-15,055.093
AIC	134,341.36	134,154.11	30,153.361	30,155.342	30,159.855	30,160.468	30,152.186
(Pseudo) R^2	0.003	0.004	0.687	0.687	0.687	0.687	0.687
Supplier-dominated	0.4203***	0.4726***	-0.0259	-0.0135	-0.0096	0.0255	0.0293*
manufacturing	(0.1606)	(0.1790)	(0.0300)	(0.0277)	(0.0257)	(0.0162)	(0.0164)
Log likelihood	-262,123.88	-261,221.11	-44,350.203	-44,328.535	-44,318.062	-44,241.904	-44,240.446
AIC	524,251.75	522,468.21	88,724.407	88,683.069	88,674.124	88,523.808	88,522.892
(Pseudo) R^2	0.013	0.017	0.827	0.827	0.827	0.827	0.827
Scale-intensive	0.1883**	0.2048**	-0.0082	-0.0017	0.0005	0.0173	0.0298*
manufacturing	(0.0891)	(0.0968)	(0.0221)	(0.0208)	(0.0204)	(0.0159)	(0.0159)
Log likelihood	-180,721.02	-180,487.8	-43,945.954	-43,937.166	-43,926.865	-43,895.815	-43,877.996
AIC	361,446.03	361,001.6	87,915.908	87,900.331	87,891.731	87,831.631	87,797.992
(Pseudo) R^2	0.003	0.004	0.745	0.745	0.745	0.745	0.745
Specialized supplier	0.1382	0.1946*	-0.0757*	-0.0643	-0.0606	-0.0389	-0.0216
manufacturing	(0.0952)	(0.1059)	(0.0406)	(0.0414)	(0.0402)	(0.0344)	(0.0349)
Log likelihood	-70,670.419	-70,339.777	-22,352.337	-22,341.858	-22,339.123	-22,324.672	-22,314.976
AIC	141,344.84	140,705.55	44,728.674	44,709.717	44,716.246	44,689.344	44,671.953
(Pseudo) R^2	0.001	0.006	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive	1.0154***	1.0017***	0.0702***	0.0676***	0.0675***	0.0681***	0.0767***
business services	(0.2606)	(0.2837)	(0.0187)	(0.0192)	(0.0195)	(0.0204)	(0.0206)
Log likelihood	-2,149,644	-2,101,726	-66,043.874	-66,039.401	-66,023.344	-66,023.236	-65,976.98
AIC	4,299,293	4,203,478	132,111.75	132,104.8	132,084.69	132,086.47	131,995.96
(Pseudo) R^2	0.059	0.080	0.971	0.971	0.971	0.971	0.971
Supplier-dominated	0.6509***	0.6645***	0.0154	0.0206	0.0214	0.0468***	0.0443***
services	(0.2095)	(0.2294)	(0.0208)	(0.0208)	(0.0197)	(0.0156)	(0.0161)
Log likelihood	-3,727,469	-3,685,433	-83,899.544	-83,860.739	-83,676.724	-83,298.07	-83,291.078
AIC	7,454,941	7,370,891	167,823.09	167,747.48	167,391.45	166,636.14	166,624.16
(Pseudo) R^2	0.029	0.040	0.978	0.978	0.978	0.978	0.978
Physical network	0.5097***	0.5526***	0.0254	0.0098	0.0138	0.0286	0.0306
services	(0.1526)	(0.1696)	(0.0271)	(0.0262)	(0.0246)	(0.0198)	(0.0202)
Log likelihood	-800,715.94	-799,211.61	-62,712.609	-62,548.313	-62,496.55	-62,440.166	-62,438.766
AIC	1,601,436	1,598,449	125,449.22	125,122.63	125,031.1	124,920.33	124,919.53
(Pseudo) R^2	0.021	0.023	0.923	0.923	0.923	0.923	0.923
Information network	1.1725***	1.2351***	0.3281***	0.2940***	0.2976***	0.2783***	0.2666***
services	(0.2961)	(0.3320)	(0.0776)	(0.0826)	(0.0827)	(0.0792)	(0.0786)
Log likelihood	-529,822.14	-526,875	-40,591.206	-40,501.26	-40,392.991	-40,374.71	-40,362.374
AIC	1,059,648	1,053,776	81,206.412	81,028.52	80,823.982	80,789.421	80,766.747
(Pseudo) R^2	0.062	0.067	0.925	0.925	0.925	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 10: Regressions for firm location across industries on UASs in **Business, Management & Services** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based manufacturing	0.1619	0.2345	-0.0140	-0.0166	-0.0130	-0.0108	0.0192
	(0.1304)	(0.1719)	(0.0590)	(0.0591)	(0.0590)	(0.0597)	(0.0749)
Log likelihood	-67,270.559	-67,134.401	-15,067.066	-15,066.975	-15,063.79	-15,063.553	-15,061.831
AIC	134,545.12	134,294.8	30,158.132	30,159.949	30,165.58	30,167.105	30,165.662
(Pseudo) R^2	0.001	0.003	0.687	0.687	0.687	0.687	0.687
Supplier-dominated manufacturing	0.2881***	0.4022***	-0.0380*	-0.0254	-0.0240	-0.0034	-0.0062
	(0.0740)	(0.1095)	(0.0221)	(0.0199)	(0.0195)	(0.0167)	(0.0196)
Log likelihood	-263,550.14	-262,292.58	-44,348.408	-44,327.225	-44,316.631	-44,244.519	-44,244.468
AIC	527,104.28	524,611.16	88,720.816	88,680.45	88,671.262	88,529.038	88,530.935
(Pseudo) R^2	0.008	0.013	0.827	0.827	0.827	0.827	0.827
Scale-intensive manufacturing	0.1578***	0.1958***	-0.0712***	-0.0649***	-0.0601***	-0.0517***	-0.0237
	(0.0534)	(0.0716)	(0.0195)	(0.0189)	(0.0189)	(0.0179)	(0.0208)
Log likelihood	-180,739.03	-180,461.13	-43,930.583	-43,924.458	-43,916.232	-43,889.076	-43,882.63
AIC	361,482.05	360,948.25	87,885.166	87,874.915	87,870.465	87,818.152	87,807.259
(Pseudo) R^2	0.003	0.005	0.745	0.745	0.745	0.745	0.745
Specialized supplier manufacturing	0.2549***	0.4638***	-0.1095***	-0.0931**	-0.0890**	-0.0779**	-0.0064
	(0.0590)	(0.0900)	(0.0380)	(0.0392)	(0.0391)	(0.0372)	(0.0435)
Log likelihood	-70,397.285	-69,666.003	-22,349.507	-22,339.903	-22,337.338	-22,321.943	-22,313.532
AIC	140,798.57	139,358.01	44,723.013	44,705.806	44,712.677	44,683.886	44,669.063
(Pseudo) R^2	0.005	0.015	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive business services	1.0012***	1.0307***	-0.0025	-0.0078	-0.0067	-0.0098	0.0128
	(0.1311)	(0.1847)	(0.0206)	(0.0204)	(0.0207)	(0.0211)	(0.0229)
Log likelihood	-2,156,542	-2,123,567	-66,135.42	-66,121.681	-66,103.959	-66,099.179	-66,090.182
AIC	4,313,089	4,247,160	132,294.84	132,269.36	132,245.92	132,238.36	132,222.36
(Pseudo) R^2	0.056	0.070	0.971	0.971	0.971	0.971	0.971
Supplier-dominated services	0.5464***	0.5825***	0.0527***	0.0594***	0.0536***	0.0699***	0.0712***
	(0.1050)	(0.1469)	(0.0161)	(0.0159)	(0.0157)	(0.0135)	(0.0155)
Log likelihood	-3,748,349	-3,715,639	-83,822.772	-83,771.51	-83,611.526	-83,248.236	-83,248.137
AIC	7,496,701	7,431,304	167,669.54	167,569.02	167,261.05	166,536.47	166,538.27
(Pseudo) R^2	0.024	0.032	0.978	0.978	0.978	0.978	0.978
Physical network services	0.4736***	0.6404***	0.0485**	0.0284	0.0274	0.0361*	0.0583***
	(0.0722)	(0.1076)	(0.0214)	(0.0212)	(0.0226)	(0.0212)	(0.0206)
Log likelihood	-799,944.94	-794,333.6	-62,699.325	-62,542.05	-62,492.325	-62,439.477	-62,431.053
AIC	1,599,894	1,588,693	125,422.65	125,110.1	125,022.65	124,918.95	124,904.11
(Pseudo) R^2	0.022	0.029	0.923	0.923	0.923	0.923	0.923
Information network services	0.9551***	1.1788***	0.4182***	0.3783***	0.3590***	0.3357***	0.3798***
	(0.1575)	(0.2281)	(0.0632)	(0.0650)	(0.0657)	(0.0622)	(0.0663)
Log likelihood	-542,501.03	-538,902.11	-40,654.331	-40,535.483	-40,463.197	-40,419.704	-40,413.015
AIC	1,085,006	1,077,830	81,332.662	81,096.965	80,964.395	80,879.407	80,868.031
(Pseudo) R^2	0.040	0.046	0.924	0.925	0.925	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 11: Regressions for firm location across industries on UASs in **Architecture, Construction & Planning** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based	0.1168	0.1522	-0.0628	-0.0642	-0.0593	-0.0600	-0.0485
manufacturing	(0.1493)	(0.1841)	(0.0400)	(0.0401)	(0.0406)	(0.0407)	(0.0438)
Log likelihood	-67,316.958	-67,217.069	-15,064.307	-15,064.145	-15,061.397	-15,061.079	-15,060.234
AIC	134,637.92	134,460.14	30,152.615	30,154.291	30,160.794	30,162.158	30,162.469
(Pseudo) R^2	0.001	0.002	0.687	0.687	0.687	0.687	0.687
Supplier-dominated	0.2208***	0.2891***	-0.0020	0.0001	0.0026	-0.0041	-0.0036
manufacturing	(0.0806)	(0.1020)	(0.0171)	(0.0178)	(0.0173)	(0.0141)	(0.0160)
Log likelihood	-264,412.75	-263,573.2	-44,353.261	-44,329.341	-44,318.426	-44,244.465	-44,244.455
AIC	528,829.49	527,172.41	88,730.522	88,684.682	88,674.853	88,528.93	88,530.91
(Pseudo) R^2	0.005	0.008	0.827	0.827	0.827	0.827	0.827
Scale-intensive	0.2041***	0.2459***	-0.0507***	-0.0497***	-0.0467***	-0.0496***	-0.0331*
manufacturing	(0.0538)	(0.0663)	(0.0150)	(0.0154)	(0.0154)	(0.0154)	(0.0172)
Log likelihood	-180,370.95	-180,007.82	-43,934.909	-43,926.325	-43,917.47	-43,886.327	-43,879.353
AIC	360,745.9	360,041.63	87,893.819	87,878.65	87,872.94	87,812.655	87,800.707
(Pseudo) R^2	0.005	0.007	0.745	0.745	0.745	0.745	0.745
Specialized supplier	0.2718***	0.4124***	-0.0818**	-0.0817**	-0.0789**	-0.0815**	-0.0483
manufacturing	(0.0597)	(0.0800)	(0.0323)	(0.0334)	(0.0330)	(0.0325)	(0.0358)
Log likelihood	-70,348.769	-69,760.334	-22,350.699	-22,338.559	-22,335.931	-22,318.788	-22,311.712
AIC	140,701.54	139,546.67	44,725.398	44,703.119	44,709.862	44,677.576	44,665.424
(Pseudo) R^2	0.006	0.014	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive	0.5750***	0.5292***	-0.0287**	-0.0280**	-0.0291**	-0.0277*	-0.0230
business services	(0.1400)	(0.1627)	(0.0142)	(0.0140)	(0.0139)	(0.0144)	(0.0155)
Log likelihood	-2,236,148	-2,189,515	-66,112.14	-66,100.049	-66,080.761	-66,079.576	-66,072.08
AIC	4,472,300	4,379,055	132,248.28	132,226.1	132,199.52	132,199.15	132,186.16
(Pseudo) R^2	0.021	0.041	0.971	0.971	0.971	0.971	0.971
Supplier-dominated	0.3363***	0.3365**	0.0235*	0.0239*	0.0211	0.0134	0.0046
services	(0.1156)	(0.1377)	(0.0141)	(0.0140)	(0.0129)	(0.0123)	(0.0140)
Log likelihood	-3,803,123	-3,763,254	-83,875.97	-83,844.409	-83,670.14	-83,380.293	-83,344.033
AIC	7,606,251	7,526,534	167,775.94	167,714.82	167,378.28	166,800.59	166,730.07
(Pseudo) R^2	0.009	0.020	0.978	0.978	0.978	0.978	0.978
Physical network	0.3365***	0.4099***	0.0464**	0.0422**	0.0423**	0.0397**	0.0457**
services	(0.0840)	(0.1063)	(0.0202)	(0.0188)	(0.0190)	(0.0191)	(0.0205)
Log likelihood	-808,586.29	-806,498.99	-62,684.888	-62,518.646	-62,468.59	-62,424.635	-62,420.626
AIC	1,617,177	1,613,024	125,393.78	125,063.29	124,975.18	124,889.27	124,883.25
(Pseudo) R^2	0.011	0.014	0.923	0.923	0.923	0.923	0.923
Information network	0.4989**	0.5164**	0.0758	0.0673	0.0571	0.0846**	0.0555
services	(0.1984)	(0.2396)	(0.0520)	(0.0471)	(0.0459)	(0.0420)	(0.0488)
Log likelihood	-558,038.36	-555,979.02	-41,002.81	-40,815.682	-40,713.175	-40,610.165	-40,565.414
AIC	1,116,081	1,111,984	82,029.621	81,657.364	81,464.35	81,260.331	81,172.829
(Pseudo) R^2	0.012	0.016	0.924	0.924	0.924	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 12: Regressions for firm location across industries on UASs in **Design** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based	0.5677***	0.6578***	0.0039	0.0025	0.0030	0.0055	0.0213
manufacturing	(0.1480)	(0.1740)	(0.0386)	(0.0392)	(0.0385)	(0.0394)	(0.0428)
Log likelihood	-66,257.409	-65,999.508	-15,067.154	-15,067.105	-15,063.866	-15,063.587	-15,061.434
AIC	132,518.82	132,025.02	30,158.307	30,160.209	30,165.732	30,167.174	30,164.868
(Pseudo) R^2	0.016	0.020	0.687	0.687	0.687	0.687	0.687
Supplier-dominated	0.4189***	0.4921***	-0.0455*	-0.0341*	-0.0327*	-0.0071	-0.0075
manufacturing	(0.1224)	(0.1451)	(0.0233)	(0.0206)	(0.0193)	(0.0144)	(0.0150)
Log likelihood	-261,516.2	-260,307.32	-44,343.381	-44,323.948	-44,313.555	-44,244.334	-44,244.328
AIC	523,036.39	520,640.64	88,710.761	88,673.895	88,665.111	88,528.669	88,530.655
(Pseudo) R^2	0.016	0.020	0.827	0.827	0.827	0.827	0.827
Scale-intensive	0.2091***	0.2344***	-0.0641***	-0.0583***	-0.0563***	-0.0454***	-0.0337**
manufacturing	(0.0727)	(0.0827)	(0.0178)	(0.0168)	(0.0167)	(0.0149)	(0.0154)
Log likelihood	-180,431.76	-180,146.15	-43,929.056	-43,923.302	-43,914.032	-43,888.652	-43,880.529
AIC	360,867.51	360,318.29	87,882.113	87,872.604	87,866.064	87,817.304	87,803.058
(Pseudo) R^2	0.005	0.006	0.745	0.745	0.745	0.745	0.745
Specialized supplier	0.2501***	0.3399***	-0.1397***	-0.1266***	-0.1256***	-0.1116***	-0.0921***
manufacturing	(0.0774)	(0.0920)	(0.0344)	(0.0352)	(0.0346)	(0.0315)	(0.0324)
Log likelihood	-70,444.155	-69,992.032	-22,336.192	-22,328.4	-22,325.518	-22,312.675	-22,305.952
AIC	140,892.31	140,010.06	44,696.383	44,682.8	44,689.035	44,665.349	44,653.905
(Pseudo) R^2	0.004	0.011	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive	1.0236***	1.0222***	-0.0342*	-0.0393**	-0.0411**	-0.0461**	-0.0414*
business services	(0.2080)	(0.2381)	(0.0204)	(0.0198)	(0.0198)	(0.0208)	(0.0227)
Log likelihood	-2,135,560	-2,090,873	-66,116.078	-66,097.136	-66,077.283	-66,067.168	-66,063.043
AIC	4,271,124	4,181,772	132,256.16	132,220.27	132,192.57	132,174.34	132,168.09
(Pseudo) R^2	0.065	0.084	0.971	0.971	0.971	0.971	0.971
Supplier-dominated	0.6748***	0.7046***	0.0198	0.0249	0.0232	0.0431***	0.0366**
services	(0.1617)	(0.1874)	(0.0179)	(0.0172)	(0.0168)	(0.0142)	(0.0151)
Log likelihood	-3,701,539	-3,659,733	-83,892.083	-83,851.567	-83,672.828	-83,309.528	-83,290.292
AIC	7,403,082	7,319,492	167,808.17	167,729.13	167,383.66	166,659.06	166,622.58
(Pseudo) R^2	0.036	0.047	0.978	0.978	0.978	0.978	0.978
Physical network	0.5879***	0.6676***	0.0210	0.0014	0.0004	0.0101	0.0093
services	(0.1132)	(0.1356)	(0.0223)	(0.0231)	(0.0223)	(0.0225)	(0.0234)
Log likelihood	-790,921.67	-787,489.58	-62,715.654	-62,549.705	-62,499.279	-62,449.939	-62,449.86
AIC	1,581,847	1,575,005	125,455.31	125,125.41	125,036.56	124,939.88	124,941.72
(Pseudo) R^2	0.033	0.037	0.923	0.923	0.923	0.923	0.923
Information network	0.9477***	1.0098***	0.1576*	0.1181	0.1098	0.0816	0.0362
services	(0.2665)	(0.3141)	(0.0865)	(0.0827)	(0.0806)	(0.0861)	(0.0956)
Log likelihood	-540,659.27	-538,053.31	-40,941.78	-40,790.935	-40,688.419	-40,627.166	-40,557.61
AIC	1,081,323	1,076,133	81,907.561	81,607.87	81,414.839	81,294.333	81,157.22
(Pseudo) R^2	0.043	0.048	0.924	0.924	0.924	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 13: Regressions for firm location across industries on UASs in **Engineering & IT** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based	0.3719***	0.5279***	-0.1195***	-0.1203***	-0.1190***	-0.1180**	-0.0991*
manufacturing	(0.1049)	(0.1537)	(0.0446)	(0.0451)	(0.0454)	(0.0458)	(0.0522)
Log likelihood	-66,871.567	-66,573.235	-15,059.556	-15,059.422	-15,056.392	-15,056.323	-15,055.172
AIC	133,747.13	133,172.47	30,143.112	30,144.843	30,150.784	30,152.647	30,152.345
(Pseudo) R^2	0.007	0.012	0.687	0.687	0.687	0.687	0.687
Supplier-dominated	0.2386***	0.3427***	-0.0378*	-0.0316	-0.0291	-0.0101	-0.0115
manufacturing	(0.0787)	(0.1138)	(0.0225)	(0.0204)	(0.0198)	(0.0165)	(0.0201)
Log likelihood	-264,206.65	-263,099.74	-44,347.742	-44,325.49	-44,315.284	-44,244.184	-44,244.164
AIC	528,417.3	526,225.47	88,719.485	88,676.979	88,668.567	88,528.369	88,530.327
(Pseudo) R^2	0.005	0.010	0.827	0.827	0.827	0.827	0.827
Scale-intensive	0.2393***	0.3122***	-0.0839***	-0.0809***	-0.0782***	-0.0705***	-0.0481**
manufacturing	(0.0503)	(0.0704)	(0.0178)	(0.0173)	(0.0174)	(0.0166)	(0.0194)
Log likelihood	-180,024.85	-179,489.92	-43,922.502	-43,915.185	-43,906.707	-43,880.63	-43,874.939
AIC	360,053.7	359,005.84	87,869.003	87,856.371	87,851.414	87,801.261	87,791.878
(Pseudo) R^2	0.007	0.010	0.745	0.745	0.745	0.745	0.745
Specialized supplier	0.2692***	0.4814***	-0.1563***	-0.1502***	-0.1473***	-0.1379***	-0.1053**
manufacturing	(0.0570)	(0.0898)	(0.0394)	(0.0392)	(0.0392)	(0.0385)	(0.0467)
Log likelihood	-70,358.275	-69,615.769	-22,337.193	-22,326.666	-22,324.512	-22,310.148	-22,307.062
AIC	140,720.55	139,257.54	44,698.386	44,679.333	44,687.025	44,660.297	44,656.124
(Pseudo) R^2	0.005	0.016	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive	0.6992***	0.6632***	-0.0883***	-0.0903***	-0.0925***	-0.0967***	-0.0984***
business services	(0.1705)	(0.2198)	(0.0232)	(0.0227)	(0.0230)	(0.0234)	(0.0273)
Log likelihood	-2,217,815	-2,177,395	-66,036.559	-66,019.049	-65,997.932	-65,985.552	-65,985.388
AIC	4,435,634	4,354,815	132,097.12	132,064.1	132,033.86	132,011.1	132,012.78
(Pseudo) R^2	0.029	0.047	0.971	0.971	0.971	0.971	0.971
Supplier-dominated	0.4063***	0.4220***	0.0216	0.0236	0.0196	0.0337*	0.0197
services	(0.1208)	(0.1604)	(0.0198)	(0.0194)	(0.0189)	(0.0174)	(0.0234)
Log likelihood	-3,787,888	-3,750,924	-83,892.367	-83,858.385	-83,682.829	-83,348.247	-83,321.542
AIC	7,575,781	7,501,873	167,808.73	167,742.77	167,403.66	166,736.49	166,685.08
(Pseudo) R^2	0.013	0.023	0.978	0.978	0.978	0.978	0.978
Physical network	0.3130***	0.4146***	0.0147	0.0041	0.0043	0.0110	0.0135
services	(0.0862)	(0.1230)	(0.0252)	(0.0257)	(0.0261)	(0.0271)	(0.0339)
Log likelihood	-809,937.84	-807,413.54	-62,719.646	-62,549.525	-62,499.062	-62,449.954	-62,449.716
AIC	1,619,880	1,614,853	125,463.29	125,125.05	125,036.12	124,939.91	124,941.43
(Pseudo) R^2	0.010	0.013	0.923	0.923	0.923	0.923	0.923
Information network	0.4902**	0.5160*	0.0253	0.0005	-0.0150	-0.0370	-0.1263
services	(0.2348)	(0.3120)	(0.1126)	(0.1084)	(0.1069)	(0.1077)	(0.1286)
Log likelihood	-558,495.99	-556,691.05	-41,034.023	-40,842.132	-40,731.184	-40,645.952	-40,534.068
AIC	1,116,996	1,113,408	82,092.045	81,710.264	81,500.368	81,331.904	81,110.136
(Pseudo) R^2	0.011	0.015	0.924	0.924	0.924	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 14: Regressions for firm location across industries on UASs in **Music, Theater & other Arts** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based manufacturing	0.3816***	0.5141***	-0.0616	-0.0656	-0.0655	-0.0643	-0.0530
	(0.1131)	(0.1545)	(0.0502)	(0.0534)	(0.0513)	(0.0518)	(0.0531)
Log likelihood	-66,854.541	-66,580.975	-15,063.89	-15,063.539	-15,060.328	-15,060.25	-15,058.432
AIC	133,713.08	133,187.95	30,151.781	30,153.077	30,158.656	30,160.499	30,158.864
(Pseudo) R^2	0.008	0.012	0.687	0.687	0.687	0.687	0.687
Supplier-dominated manufacturing	0.2764***	0.3614***	-0.0298	-0.0161	-0.0152	0.0067	0.0108
	(0.0928)	(0.1272)	(0.0217)	(0.0191)	(0.0183)	(0.0142)	(0.0144)
Log likelihood	-263,795.43	-262,827.96	-44,347.96	-44,327.876	-44,317.17	-44,244.314	-44,243.359
AIC	527,594.87	525,681.92	88,719.921	88,681.752	88,672.34	88,528.628	88,528.717
(Pseudo) R^2	0.007	0.011	0.827	0.827	0.827	0.827	0.827
Scale-intensive manufacturing	0.1475***	0.1765**	-0.0567***	-0.0508***	-0.0482***	-0.0395***	-0.0262*
	(0.0570)	(0.0734)	(0.0162)	(0.0155)	(0.0155)	(0.0144)	(0.0145)
Log likelihood	-180,841.83	-180,596.92	-43,929.017	-43,923.814	-43,914.93	-43,888.998	-43,877.86
AIC	361,687.66	361,219.85	87,882.035	87,873.628	87,867.861	87,817.995	87,797.72
(Pseudo) R^2	0.002	0.004	0.745	0.745	0.745	0.745	0.745
Specialized supplier manufacturing	0.0917	0.2053**	-0.1655***	-0.1535***	-0.1524***	-0.1411***	-0.1258***
	(0.0629)	(0.0859)	(0.0302)	(0.0316)	(0.0314)	(0.0290)	(0.0297)
Log likelihood	-70,701.658	-70,310.503	-22,320.199	-22,314.464	-22,311.878	-22,299.944	-22,295.571
AIC	141,407.32	140,647.01	44,664.398	44,654.928	44,661.756	44,639.889	44,633.141
(Pseudo) R^2	0.001	0.006	0.593	0.593	0.593	0.594	0.594
Knowledge-intensive business services	0.9032***	0.8677***	-0.0233	-0.0294	-0.0301	-0.0335	-0.0259
	(0.1693)	(0.2196)	(0.0206)	(0.0207)	(0.0207)	(0.0214)	(0.0227)
Log likelihood	-2,167,202	-2,137,233	-66,122.968	-66,103.079	-66,084.444	-66,075.967	-66,058.915
AIC	4,334,409	4,274,492	132,269.94	132,232.16	132,206.89	132,191.93	132,159.83
(Pseudo) R^2	0.051	0.064	0.971	0.971	0.971	0.971	0.971
Supplier-dominated services	0.5941***	0.6086***	0.0227	0.0293*	0.0276*	0.0430***	0.0372***
	(0.1236)	(0.1643)	(0.0159)	(0.0158)	(0.0155)	(0.0135)	(0.0141)
Log likelihood	-3,729,494	-3,701,671	-83,878.595	-83,829.49	-83,652.68	-83,286.602	-83,266.924
AIC	7,458,993	7,403,369	167,781.19	167,684.98	167,343.36	166,613.2	166,575.85
(Pseudo) R^2	0.028	0.036	0.978	0.978	0.978	0.978	0.978
Physical network services	0.4217***	0.5269***	0.0104	-0.0110	-0.0114	-0.0042	-0.0044
	(0.0908)	(0.1246)	(0.0259)	(0.0274)	(0.0279)	(0.0288)	(0.0297)
Log likelihood	-803,713	-800,695.78	-62,720.227	-62,547.511	-62,496.928	-62,451.05	-62,451.043
AIC	1,607,430	1,601,418	125,464.45	125,121.02	125,031.86	124,942.1	124,944.09
(Pseudo) R^2	0.017	0.021	0.923	0.923	0.923	0.923	0.923
Information network services	0.7449***	0.8112***	0.0738	0.0289	0.0226	-0.0008	-0.0386
	(0.2247)	(0.3084)	(0.1045)	(0.1030)	(0.1011)	(0.1050)	(0.1134)
Log likelihood	-549,752.03	-548,201.7	-41,008.227	-40,838.052	-40,729.43	-40,650.18	-40,566.185
AIC	1,099,508	1,096,429	82,040.453	81,702.104	81,496.86	81,340.36	81,174.37
(Pseudo) R^2	0.027	0.030	0.924	0.924	0.924	0.924	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 15: Regressions for firm location across industries on UASs in **Health** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based	0.1755	0.2346	0.0148	0.0138	0.0076	0.0062	0.0128
manufacturing	(0.1737)	(0.2053)	(0.0463)	(0.0473)	(0.0463)	(0.0467)	(0.0480)
Log likelihood	-67,271.259	-67,145.97	-15,066.99	-15,066.962	-15,063.828	-15,063.58	-15,061.894
AIC	134,546.52	134,317.94	30,157.98	30,159.923	30,165.656	30,167.16	30,165.787
(Pseudo) R^2	0.001	0.003	0.687	0.687	0.687	0.687	0.687
Supplier-dominated	-0.0034	-0.0077	0.0014	0.0104	0.0086	-0.0056	-0.0048
manufacturing	(0.1177)	(0.1354)	(0.0251)	(0.0255)	(0.0235)	(0.0163)	(0.0163)
Log likelihood	-265,650.48	-265,311.94	-44,353.273	-44,328.766	-44,318.073	-44,244.393	-44,244.319
AIC	531,304.97	530,649.87	88,730.546	88,683.532	88,674.145	88,528.785	88,530.637
(Pseudo) R^2	0.000	0.001	0.827	0.827	0.827	0.827	0.827
Scale-intensive	-0.0345	-0.0567	-0.0211	-0.0169	-0.0157	-0.0204	-0.0096
manufacturing	(0.0672)	(0.0769)	(0.0182)	(0.0184)	(0.0183)	(0.0161)	(0.0161)
Log likelihood	-181,272.92	-181,071.54	-43,944.129	-43,935.858	-43,925.736	-43,894.967	-43,878.108
AIC	362,549.84	362,169.08	87,912.259	87,897.717	87,889.472	87,829.934	87,798.215
(Pseudo) R^2	0.000	0.001	0.745	0.745	0.745	0.745	0.745
Specialized supplier	-0.2296***	-0.1831**	-0.0825**	-0.0752**	-0.0751**	-0.0814**	-0.0696**
manufacturing	(0.0794)	(0.0912)	(0.0363)	(0.0353)	(0.0348)	(0.0328)	(0.0331)
Log likelihood	-70,532.221	-70,358.724	-22,350.285	-22,339.478	-22,336.309	-22,318.442	-22,312.457
AIC	141,068.44	140,743.45	44,724.571	44,704.956	44,710.618	44,676.885	44,666.914
(Pseudo) R^2	0.003	0.005	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive	0.2260	0.0127	-0.0137	-0.0161	-0.0155	-0.0133	-0.0102
business services	(0.2310)	(0.2564)	(0.0213)	(0.0210)	(0.0207)	(0.0215)	(0.0217)
Log likelihood	-2,277,401	-2,224,909	-66,131.312	-66,116.446	-66,099.11	-66,096.282	-66,088.164
AIC	4,554,806	4,449,843	132,286.62	132,258.89	132,236.22	132,232.56	132,218.33
(Pseudo) R^2	0.003	0.026	0.971	0.971	0.971	0.971	0.971
Supplier-dominated	0.1881	0.0734	-0.0048	-0.0014	-0.0022	-0.0129	-0.0210
services	(0.1683)	(0.1928)	(0.0193)	(0.0189)	(0.0179)	(0.0154)	(0.0154)
Log likelihood	-3,829,234	-3,792,466	-83,909.7	-83,880.36	-83,697.386	-83,381.964	-83,289.721
AIC	7,658,472	7,584,958	167,843.4	167,786.72	167,432.77	166,803.93	166,621.44
(Pseudo) R^2	0.002	0.012	0.978	0.978	0.978	0.978	0.978
Physical network	0.0355	0.0282	0.0038	-0.0118	-0.0122	-0.0192	-0.0225
services	(0.1222)	(0.1408)	(0.0290)	(0.0313)	(0.0309)	(0.0301)	(0.0297)
Log likelihood	-817,824.21	-817,727.41	-62,722.031	-62,547.335	-62,496.747	-62,445.204	-62,439.96
AIC	1,635,652	1,635,481	125,468.06	125,120.67	125,031.49	124,930.41	124,921.92
(Pseudo) R^2	0.000	0.000	0.923	0.923	0.923	0.923	0.923
Information network	0.1604	0.0529	-0.0772	-0.1097	-0.1096	-0.0843	-0.1182
services	(0.3015)	(0.3499)	(0.0881)	(0.0791)	(0.0810)	(0.0803)	(0.0828)
Log likelihood	-564,306.55	-562,124.24	-41,005.37	-40,781.619	-40,672.538	-40,616.901	-40,457.382
AIC	1,128,617	1,124,274	82,034.739	81,589.237	81,383.076	81,273.802	80,956.763
(Pseudo) R^2	0.001	0.005	0.924	0.924	0.924	0.925	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 16: Regressions for firm location across industries on UASs in **Social Work** with step-wise inclusion of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Science-based manufacturing	0.0108	0.0375	-0.0503	-0.0589	-0.0528	-0.0514	-0.0447
	(0.1410)	(0.1752)	(0.0447)	(0.0447)	(0.0438)	(0.0445)	(0.0458)
Log likelihood	-67,365.558	-67,282.425	-15,064.929	-15,064.358	-15,061.742	-15,061.613	-15,060.297
AIC	134,735.12	134,590.85	30,153.857	30,154.716	30,161.484	30,163.225	30,162.593
(Pseudo) R^2	0.000	0.001	0.687	0.687	0.687	0.687	0.687
Supplier-dominated manufacturing	0.3618***	0.4653***	-0.0540***	-0.0410**	-0.0397**	-0.0205	-0.0215
	(0.0868)	(0.1218)	(0.0191)	(0.0170)	(0.0162)	(0.0132)	(0.0133)
Log likelihood	-262,463.22	-261,209.91	-44,335.827	-44,319.862	-44,309.687	-44,242.296	-44,242.239
AIC	524,930.44	522,445.82	88,695.655	88,665.724	88,657.375	88,524.591	88,526.477
(Pseudo) R^2	0.012	0.017	0.827	0.827	0.827	0.827	0.827
Scale-intensive manufacturing	0.2037***	0.2410***	-0.0573***	-0.0509***	-0.0480***	-0.0396***	-0.0283*
	(0.0567)	(0.0728)	(0.0163)	(0.0153)	(0.0152)	(0.0143)	(0.0145)
Log likelihood	-180,432.88	-180,146.8	-43,929.004	-43,924.195	-43,915.445	-43,889.176	-43,880.456
AIC	360,869.76	360,319.6	87,882.007	87,874.389	87,868.889	87,818.353	87,802.913
(Pseudo) R^2	0.005	0.006	0.745	0.745	0.745	0.745	0.745
Specialized supplier manufacturing	0.2675***	0.4413***	-0.1037***	-0.0896***	-0.0869***	-0.0754***	-0.0525*
	(0.0606)	(0.0855)	(0.0296)	(0.0315)	(0.0311)	(0.0289)	(0.0295)
Log likelihood	-70,382.837	-69,730.234	-22,344.041	-22,335.828	-22,333.279	-22,319.013	-22,310.839
AIC	140,769.67	139,486.47	44,712.083	44,697.655	44,704.558	44,678.026	44,663.678
(Pseudo) R^2	0.005	0.014	0.593	0.593	0.593	0.593	0.593
Knowledge-intensive business services	0.9644***	0.9217***	-0.0112	-0.0175	-0.0180	-0.0204	-0.0150
	(0.1640)	(0.2141)	(0.0180)	(0.0178)	(0.0177)	(0.0181)	(0.0190)
Log likelihood	-2,151,101	-2,126,354	-66,132.418	-66,115.129	-66,096.861	-66,090.568	-66,079.956
AIC	4,302,206	4,252,735	132,288.84	132,256.26	132,231.72	132,221.14	132,201.91
(Pseudo) R^2	0.058	0.069	0.971	0.971	0.971	0.971	0.971
Supplier-dominated services	0.6333***	0.6407***	0.0162	0.0235*	0.0214	0.0347***	0.0291**
	(0.1195)	(0.1592)	(0.0148)	(0.0141)	(0.0137)	(0.0119)	(0.0122)
Log likelihood	-3,714,953	-3,691,775	-83,894.033	-83,847.208	-83,670.135	-83,321.315	-83,300.553
AIC	7,429,909	7,383,576	167,812.07	167,720.42	167,378.27	166,682.63	166,643.11
(Pseudo) R^2	0.032	0.038	0.978	0.978	0.978	0.978	0.978
Physical network services	0.5049***	0.6338***	0.0242	0.0015	0.0007	0.0072	0.0076
	(0.0858)	(0.1200)	(0.0244)	(0.0230)	(0.0230)	(0.0240)	(0.0253)
Log likelihood	-797,531.87	-793,218.56	-62,710.999	-62,549.69	-62,499.272	-62,450.437	-62,450.416
AIC	1,595,068	1,586,463	125,446	125,125.38	125,036.54	124,940.87	124,942.83
(Pseudo) R^2	0.025	0.030	0.923	0.923	0.923	0.923	0.923
Information network services	0.8102***	0.8844***	0.0893	0.0399	0.0359	0.0181	-0.0146
	(0.2140)	(0.2985)	(0.1065)	(0.1068)	(0.1038)	(0.1058)	(0.1146)
Log likelihood	-547,005.4	-545,645.5	-40,993.113	-40,834.191	-40,725.509	-40,648.585	-40,580.449
AIC	1,094,015	1,091,317	82,010.226	81,694.383	81,489.018	81,337.171	81,202.897
(Pseudo) R^2	0.032	0.034	0.924	0.924	0.924	0.924	0.925
Year Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes	Yes
Population Density	No	No	No	Yes	Yes	Yes	Yes
Land Use	No	No	No	No	Yes	Yes	Yes
Infrastructure	No	No	No	No	No	Yes	Yes
UAS in other fields	No	No	No	No	No	No	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows regression results for regressions of the number of firms in different industries (rows). Thus, each coefficient represents a different regression. Throughout columns (1) to (7), control variables are included step-by-step as indicated in the bottom of the table. AIC: Akaike information criterion. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix D Results Further Analyses

Table 17: Regressions of firms in different industries on UASs in all fields (instead of separately including them)

	Science-based	Supplier-dominated	Scale-intensive	Specialized supplier	Knowledge-intensive	Supplier-dominated	Physical network	Information network
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemistry & Life Sciences	0.1128***	0.0295*	0.0425***	-0.0073	0.0855***	0.0266	0.0208	0.2259***
	(0.0430)	(0.0168)	(0.0160)	(0.0329)	(0.0196)	(0.0166)	(0.0218)	(0.0652)
Business, Management & Services	0.0104	0.0136	-0.0091	0.0341	0.0443*	0.0572***	0.0349	0.3855***
	(0.0609)	(0.0213)	(0.0209)	(0.0440)	(0.0268)	(0.0209)	(0.0353)	(0.1252)
Architecture, Construction & Planning	-0.0130	0.0000	-0.0191	-0.0044	0.0052	-0.0114	0.0496***	0.1001**
	(0.0461)	(0.0198)	(0.0190)	(0.0378)	(0.0148)	(0.0152)	(0.0173)	(0.0399)
Design	0.0648*	-0.0162	-0.0153	-0.0227	-0.0270	0.0089	0.0010	0.0474
	(0.0383)	(0.0149)	(0.0162)	(0.0313)	(0.0185)	(0.0150)	(0.0167)	(0.0413)
Engineering & IT	-0.1251**	-0.0178	-0.0495**	-0.0896*	-0.1142***	0.0024	-0.0330	-0.2552***
	(0.0597)	(0.0232)	(0.0204)	(0.0482)	(0.0245)	(0.0247)	(0.0298)	(0.0944)
Music, Theater & other Arts	-0.0681	0.0261*	-0.0131	-0.0959***	-0.0162	0.0282*	-0.0155	-0.0446
	(0.0605)	(0.0156)	(0.0164)	(0.0288)	(0.0204)	(0.0153)	(0.0245)	(0.0564)
Social Work	-0.0528	-0.0332**	-0.0236	-0.0158	-0.0101	0.0077	0.0057	-0.0256
	(0.0456)	(0.0141)	(0.0151)	(0.0292)	(0.0164)	(0.0134)	(0.0216)	(0.0732)
Health	0.0327	-0.0034	0.0023	-0.0454	0.0027	-0.0359**	-0.0238	-0.0985*
	(0.0430)	(0.0167)	(0.0157)	(0.0325)	(0.0219)	(0.0154)	(0.0246)	(0.0535)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land Use	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infrastructure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipalities	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
Observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664	26,664
(Pseudo) R^2	0.687	0.827	0.745	0.594	0.971	0.978	0.923	0.926
Log likelihood	-15,044.511	-44,235.769	-43,867.693	-22,290.586	-65,841.816	-83,100.817	-62,392.902	-40,040.658

Notes: The columns show the regression results for different industry categories (1) All industries (2) Sience-based manufacturing (3) Supplier-dominated manufacturing (4) Scale-intensive manufacturing (5) Spezialiced-suplier manufacturing (6) Knowledge-intensive business services (7) Supplier-dominated services (8) Physical network services (9) Information network services. Levels of significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 18: Regression results of firm location in different sub-sectors on UASs across all fields

	All Firms	Manufacturing sector	Service sector	Construction sector	Public administration
	(1)	(2)	(3)	(4)	(5)
UASs in all fields					
Effect	-0.0058	**-0.0573*****	**0.0422****	0.0160	**0.1378****
q-value	0.8190	0.0020	0.0350	0.4790	0.0210
Chemistry & Life Sciences					
Effect	**0.0625*****	**0.0295***	**0.0660*****	**0.0347***	**0.1867*****
q-value	0.0070	0.0840	0.0030	0.0560	0.0010
Business, Management & Services					
Effect	**0.0421***	-0.0152	**0.0775*****	**0.0396***	**0.1867*****
q-value	0.0660	0.4900	0.0010	0.0790	0.0010
Architecture, Construction & Planning					
Effect	0.0027	-0.0236	0.0069	**0.0341***	0.0548
q-value	0.9120	0.1850	0.6920	0.0640	0.4630
Design					
Effect	0.0096	-0.0249	0.0200	0.0201	0.0410
q-value	0.6920	0.1060	0.4420	0.2900	0.4630
Engineering & IT					
Effect	-0.0209	**-0.0437****	-0.0090	0.0167	-0.0904
q-value	0.5500	0.0250	0.8300	0.4630	0.1630
Music, Theater & other Arts					
Effect	-0.0018	-0.0232	0.0152	**0.0577*****	0.0413
q-value	0.9240	0.1200	0.5690	0.0020	0.4790
Health					
Effect	-0.0200	-0.0095	-0.0230	0.0266	0.0034
q-value	0.4630	0.5820	0.3680	0.2400	0.9260
Social Work					
Effect	0.0010	**-0.0285***	0.0131	**0.0323****	0.0522
q-value	0.9260	0.0610	0.5690	0.0450	0.3940
n	2,222	2,222	2,222	2,222	2,222
N	26,664	26,664	26,664	26,664	26,664

Notes: The table shows results of separate regressions of Equation (1). Rows correspond to UASs (overall and by field), columns to: (1) all firms, (2) the manufacturing sector, (3) the service sector, (4) the construction sector and (5) the public administration. For clarity, **significant** coefficients are in **bold** and significance levels are indicated as follows: * $q<0.10$, ** $q<0.05$, *** $q<0.01$. To control for multiple hypotheses testing, the reported q-values are "sharpened false discovery rate q-values" as suggested by Anderson (2008). Regressions include municipality and year fixed effects, control for population density, land use, the strength of regional infrastructure and for nearby UASs in other fields. n: number of municipalities, N: overall observations.

Table 19: Different p-values for main results (multiple hypotheses testing)

	Manufacturing				Services			
	Science-based	Supplier-dominated	Scale-intensive	Specialized supplier	Knowledge-intensive	Supplier-dominated	Physical network	Information network
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemisty & Life Sciences								
Effect	0.0915	0.0293	0.0298	-0.0216	0.0767	0.0443	0.0306	0.2666
p-value	**0.0377****	**0.0739***	**0.0618***	0.5349	**0.0002*****	**0.0061*****	0.1307	**0.0007*****
q-value	0.1200	0.1550	0.1550	0.6370	**0.0040*****	**0.0400****	0.2290	**0.0070*****
p*-value	2.4114	4.7282	3.9538	34.2336	**0.0132****	0.3877	8.3635	**0.0451****
Business, Management & Services								
Effect	0.0192	-0.0062	-0.0237	-0.0064	0.0128	0.0712	0.0583	0.3798
p-value	0.7976	0.7494	0.2533	0.8826	0.5775	**0.0000*****	**0.0048*****	**0.0000*****
q-value	0.7410	0.7330	0.3700	0.8130	0.6480	**0.0010*****	**0.0360****	**0.0010*****
p*-value	51.0447	47.9620	16.2081	56.4869	36.9569	**0.0003*****	0.3059	**0.0000*****
Architecture, Construction & Planning								
Effect	-0.0485	-0.0036	-0.0331	-0.0483	-0.0230	0.0046	0.0457	0.0555
p-value	0.2691	0.8239	**0.0539***	0.1773	0.1377	0.7402	**0.0259****	0.2551
q-value	0.3830	0.7620	0.1490	0.2670	0.2290	0.7330	**0.0970***	0.3700
p*-value	17.2223	52.7295	3.4502	11.3448	8.8128	47.3710	1.6574	16.3277
Design								
Effect	0.0213	-0.0075	-0.0337	-0.0921	-0.0414	0.0366	0.0093	0.0362
p-value	0.6183	0.6193	**0.0288****	**0.0045*****	**0.0682***	**0.0153****	0.6904	0.7048
q-value	0.6800	0.6800	0.1010	**0.0360****	0.1550	**0.0740***	0.7330	0.7330
p*-value	39.5736	39.6327	1.8419	0.2874	4.3662	0.9773	44.1874	45.1072
Engineering & IT								
Effect	-0.0991	-0.0115	-0.0481	-0.1053	-0.0984	0.0197	0.0135	-0.1263
p-value	**0.0581***	0.5682	**0.0133****	**0.0241****	**0.0003*****	0.4016	0.6912	0.3261
q-value	0.1540	0.6480	**0.0700***	**0.0970***	**0.0040*****	0.5190	0.7330	0.4360
p*-value	3.7162	36.3637	0.8508	1.5450	**0.0205****	25.7021	44.2338	20.8713
Music, Theater & other Arts								
Effect	-0.0530	0.0108	-0.0262	-0.1258	-0.0259	0.0372	-0.0044	-0.0386
p-value	0.3177	0.4513	**0.0717***	**0.0000*****	0.2540	**0.0085*****	0.8822	0.7338
q-value	0.4360	0.5500	0.1550	**0.0010*****	0.3700	**0.0500***	0.8130	0.7330
p*-value	20.3312	28.8809	4.5902	**0.0015*****	16.2532	0.5470	56.4601	46.9618
Health								
Effect	0.0128	-0.0048	-0.0096	-0.0696	-0.0102	-0.0210	-0.0225	-0.1182
p-value	0.7893	0.7664	0.5539	**0.0355****	0.6392	0.1728	0.4488	0.1538
q-value	0.7410	0.7330	0.6480	0.1200	0.6930	0.2670	0.5500	0.2420
p*-value	50.5151	49.0502	35.4475	2.2740	40.9111	11.0607	28.7229	9.8413
Social Work								
Effect	-0.0447	-0.0215	-0.0283	-0.0525	-0.0150	0.0291	0.0076	-0.0146
p-value	0.3284	0.1050	**0.0520***	**0.0756***	0.4309	**0.0170****	0.7647	0.8988
q-value	0.4360	0.2090	0.1490	0.1550	0.5500	**0.0770***	0.7330	0.8170
p*-value	21.0197	6.7198	3.3250	4.8381	27.5806	1.0889	48.9387	57.5227
n	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
N	26,664	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows results of separate regressions of Equation (1). Reported p-values correspond to standard p-values of the regression coefficient. To control for multiple hypotheses testing, we show (1) q-values, i.e., "sharpened false discovery rate q-values" as suggested by Anderson (2008) and p*-values, i.e., the more conservative Bonferroni correction (Abdi, 2007). For clarity, significant coefficients are in **bold**. Significance levels are indicated with the respective test statistic, thereby showing whether the estimated coefficient is significant when the particular test statistic is used. Significance levels: * q<0.10, ** q<0.05, *** q<0.01. All regressions include municipality and year fixed effects, control for population density, land use, the strength of regional infrastructure and for nearby UASs in other fields. n represents the number of municipalities, N the overall observations.

Appendix E Results Robustness Checks

Table 20: PPML regression results of the dummy for the establishment of a UAS in a particular field on firms across different industries

	Chemistry & Life Sciences	Business, Management & Services	Design	Architecture, Construction & Planning	Engineering & IT	Music, Theater & other Arts	Health	Social Work
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Science-based manufacturing								
Effect	0.0126	0.0013	0.0025	-0.0002	0.0008	**0.0145****	0.0061	**0.0350****
q-value	0.3840	0.8530	0.8690	1.0000	0.9980	0.0250	0.8170	0.0250
Supplier-dominated manufacturing								
Effect	-0.0012	-0.0009	**0.0045***	0.0008	0.0021	**0.0035***	0.0043	0.0040
q-value	0.8530	0.1560	0.0740	0.6740	0.1240	0.0740	0.6740	0.2360
Scale-intensive manufacturing								
Effect	0.0056	-0.0003	0.0008	-0.0008	-0.0003	**0.0068****	0.0029	0.0086
q-value	0.4180	1.0000	0.9980	0.9380	1.0000	0.0380	0.8690	0.1030
Specialized supplier manufacturing								
Effect	0.0044	0.0021	0.0004	-0.0004	-0.0042	0.0078	-0.0109	0.0093
q-value	0.8690	0.5340	1.0000	1.0000	0.5420	0.5420	0.8480	0.4950
Knowledge intensive business services								
Effect	0.0001	**0.0000****	-0.0001	0.0000	0.0000	0.0000	0.0001	-0.0001
q-value	0.8530	0.0250	0.8170	0.8530	1.0000	0.9980	0.8690	0.5920
Supplier-dominated services								
Effect	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0002	-0.0002
q-value	1.0000	1.0000	1.0000	0.2360	0.5420	1.0000	0.8480	0.4480
Physical network services								
Effect	0.0001	0.0000	**0.0013***	0.0005	0.0006	**0.0015****	0.0009	0.0001
q-value	0.9350	0.9980	0.0680	0.2360	0.1560	0.0160	0.6340	1.0000
Information network services								
Effect	0.0003	0.0001	0.0004	0.0002	0.0004	0.0007	0.0012	0.0005
q-value	0.6260	0.4260	0.8340	0.5250	0.5220	0.5530	0.8480	0.8520
n	2,222	2,222	2,222	2,222	2,222	2,222	2,222	2,222
N	26,664	26,664	26,664	26,664	26,664	26,664	26,664	26,664

Notes: The table shows the coefficients for estimated changes in treatment probabilities, i.e., the establishment of a UAS in a particular field, associated with the number of firms in a particular industry as shown in Equation (2). For clarity, significant coefficients are in **bold** and significance levels are indicated as follows: * $q<0.10$, ** $q<0.05$, *** $q<0.01$. To control for multiple hypotheses testing, we use "sharpened false discovery rate q-values" as suggested by Anderson (2008). Regressions include year and municipality fixed effects, and control for population density, land use, and the strength of regional infrastructure. n represents the number of observations within one year; N, the overall observations.

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