Working Paper No. 248

Educational Backgrounds in Inventor Teams: The Role of Complementarities between Academic and Vocational Education in Team Performance

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Abstract

This paper analyzes whether inventor teams composed of members with diverse educational backgrounds, both academic and vocational, exhibit higher performance than teams with the same educational backgrounds. To exploit the different educational backgrounds among patent inventors in Switzerland, we construct a unique dataset of 35,486 inventors. This dataset links individual patenting activities from European Patent Office data from 1980–2021, with detailed biographical information obtained from LinkedIn. Using a supermodularity framework to assess complementarity, we find that inventor teams composed of members with academic and vocational backgrounds (as opposed to members with the same background) achieve higher team performance, measured by the quality of their jointly filed patents. This complementarity is even stronger in teams with at least one team member from a University of Applied Sciences. Further analysis reveals heterogeneous effects across technological fields. Overall, our findings show the importance of strategically combining different educational backgrounds in inventor teams, thereby highlighting the value of maintaining a balanced educational landscape.

Keywords: team productivity, inventor biographies, vocational education, patent quality

JEL Classification: I23, I26, M54, O32

1. Introduction

Innovation boosts economic growth, drives competitive advantage (Romer, 1990), and relies on highly skilled individuals (e.g., Bianchi & Giorcelli, 2019; Valero & Van Reenen, 2019). The traditional view was that individuals attain these skills through tertiary-level academic education (e.g., Aghion, 2008; Aghion & Howitt, 2006, Krueger & Kumar, 2004a; 2004b). However, recent research challenges this view by showing the importance of vocational education for innovation (e.g., Backes-Gellner & Lehnert, 2021; Lewis, 2023; Toner, 2010). For example, although the United Kingdom has a high share of tertiary-level academic graduates (OECD, 2024), Lewis (2020; 2023) shows that its innovation system struggles from shortcomings in its vocational workforce. In contrast, Germany and Switzerland hold leading positions in international innovation rankings,[1] likely because they combine their comparatively low shares of tertiary-level academic graduates with a high share of vocationally trained workers (Backes-Gellner & Lehnert, 2021; 2023; BFS, 2023; 2024a). These two examples show that combining thorough vocational education with academic education at the research frontier can significantly contribute to highly successful innovation systems.

Research on the contribution of vocational education to innovation focuses primarily on the composition of educational backgrounds at the firm level. This research shows that diversity in educational backgrounds, including at the academic and vocational education level, increases innovation activities (e.g., Bolli et al. 2018; Mason et al., 2020; Matthies & Thomä, 2025; McGuirk, & Jordan, 2012; Østergaard et al., 2011; Rupietta & Backes-Gellner, 2019; Rupietta et al., 2021). In addition, while research analyzing innovative team-level creativity and problem-solving tasks focuses on diversity in educational fields (e.g., natural science, social science) or educational levels (e.g., secondary, tertiary), it does not focus on educational background types such as vocational and academic (e.g., Schubert & Tavassoli, 2020; Valls et al., 2016; Yang & Choi, 2024). Therefore, the question of whether a team composition featuring individuals with both academic and vocational educational backgrounds results in complementarities (i.e., positive interaction effects) that improve team performance thus far remains unanswered.

This study examines combinations of different types of educational backgrounds in teams performing innovative tasks and analyzes which combinations yield complementarities that improve team performance. We measure the educational backgrounds of individuals who

[1] E.g., the WIPO Global Innovation Index 2024 (Dutta et al., 2024).

work together in teams and jointly filed a patent (hereafter, “inventor teams”), measuring team performance by common indicators of patent quality (e.g., number of forward citations).

The Swiss education system provides an ideal setting for our research goals. Switzerland (a) has very strong innovation performance internationally (Dutta et al., 2023; European Commission, 2025) and (b) features a high variety of educational backgrounds (BFS, 2024a; 2024b; SKBF, 2023;)—including a broad variety of academic and vocational skills—in its workforce. Specifically, we observe four types of educational backgrounds, each characterized by specific skill sets. The first two are mid-level vocational skills obtained through apprenticeship training, and high-level vocational skills obtained through several years of work experience post-apprenticeship training and combined with additional professional education. The other two are a combination of high-level vocational skills and applied academic research knowledge, from Universities of Applied Sciences (UASs), and high-level academic skills from academic universities. Individuals with these different educational backgrounds play different roles in inventor teams through differing types of creative and problem-solving capabilities. The Swiss education system thus allows us to study the extent to which different combinations of educational backgrounds in inventor teams improve team performance.

To examine whether combinations of educational background types yield complementarities that improve inventor team performance, we use two data sources and match them at the inventor team level. First, we use data from the European Patent Office’s (EPO) Worldwide Patent Statistical Database (October 2023 version), which includes detailed information on applicants and inventors of patents filed at the EPO since 1980. These data allow us to define inventor teams as all individuals who jointly filed a patent.[2] The dataset also provides three commonly used indicators for the quality of the filed patent, which we use as measures for team performance: the number of forward citations (i.e., post-patent citations), the size of the patent family (i.e., patent filed in different countries), and the number of priority claims (i.e., patent covering larger areas).

Second, to gather information on the educational background of each inventor, we use LinkedIn profiles (provided by Revelio Labs). To do so, we develop a novel algorithm to match individuals from the EPO data to their LinkedIn profiles. This procedure uses all available individual information from both the EPO and the LinkedIn data, including addresses, patent applicants, and employment histories. Our matched dataset contains novel information on the quality of jointly filed patents and on inventors’ educational backgrounds, thereby enabling us

[2] Following the innovation literature, this study focuses on patents as a measure of innovation outcomes. While we recognize that patents capture only a subset of all possible innovations, they provide a concrete and quantifiable indicator of inventive activity that aligns with our research focus on jointly filed patents.

to study the relationship between team performance and differences in the composition of team members' educational backgrounds.

To empirically analyze complementarities within inventor teams, we employ the supermodularity framework (Milgrom & Roberts, 1990; Mohnen & Röller, 2005). Researchers in the innovation literature have effectively used this approach to examine complementarities among multiple factors (e.g., Ballot et al., 2015; Guisado-González et al., 2017; Serrano-Bedia et al., 2018). As the different educational backgrounds in inventor teams contain multiple factors, the supermodularity framework is particularly well-suited for capturing the complexity of the educational backgrounds' interactions. This method thus enables us to gain detailed insights into the relationship between inventors' educational background complementarities and their team performance.

Our results show that complementarities between vocational and academic educational backgrounds indeed play a significant role within inventor teams, particularly between individuals with high-level academic skills from academic universities and individuals with mid-level vocational skills from apprenticeship training. These complementarities are especially pronounced in teams where UAS graduates are also present. Given the unique combination of vocational skills and applied academic research knowledge among UAS graduates, they act as ideal bridge builders. By promoting the exchange and combination of otherwise distinct skill sets, UAS graduates serve as moderators of effective collaboration between team members with solely academic or vocational backgrounds.

Further analyses across different technology fields demonstrate that these complementarities vary considerably by technological context. For example, in the fields of computer technology, electrical/energy, and chemical engineering, all of which are highly application-oriented fields, inventor teams benefit substantially from combining members with vocational and academic backgrounds. Conversely, in other areas, such as organic chemistry, the findings show a substitutive rather than complementary relationship, indicating that the combination of vocational and academic backgrounds appears redundant or even counterproductive. These nuanced insights show that firms' considerations depend on their technological context when assessing the combination of educational backgrounds in inventor teams.

By combining different types of educational backgrounds, particularly the role of vocational education as a complement to academic education, our study advances scholarly understanding of precisely what educational composition is optimal for inventor teams. We find that inventor teams with both vocational and academic educational backgrounds perform better than teams with only one type of educational background. If an inventor team also comprises UAS graduates—individuals whose education combines vocational and academic skills—the team performs even better. This finding shows the crucial role of UAS graduates as bridge builders between vocationally and academically trained inventors. Thus, when forming inventor teams, firms need to account for the distinct roles and functions of the potential members' different educational backgrounds.

The structure of this paper is as follows. Section 2 describes the conceptual background of our study and formulates a set of hypotheses on the effects of educational complementarities in inventor teams on inventor team performance. Section 3 describes the data sources and matching procedure. Section 4 details the methodology, including the supermodularity framework used for analyzing complementarities. Section 5 presents the main results of the complementarity analysis. Section 6 presents further analysis across different technologies. Section 7 concludes by discussing both the findings and their implications.

2. Conceptual background

In this section, we first outline the Swiss educational system, with a focus on its distinct educational variety and potential contribution to innovation. Second, we review the literature on the impact of vocational education and educational diversity in teams on innovation. Third, we derive testable hypotheses on the complementarities between different educational backgrounds in inventor teams.

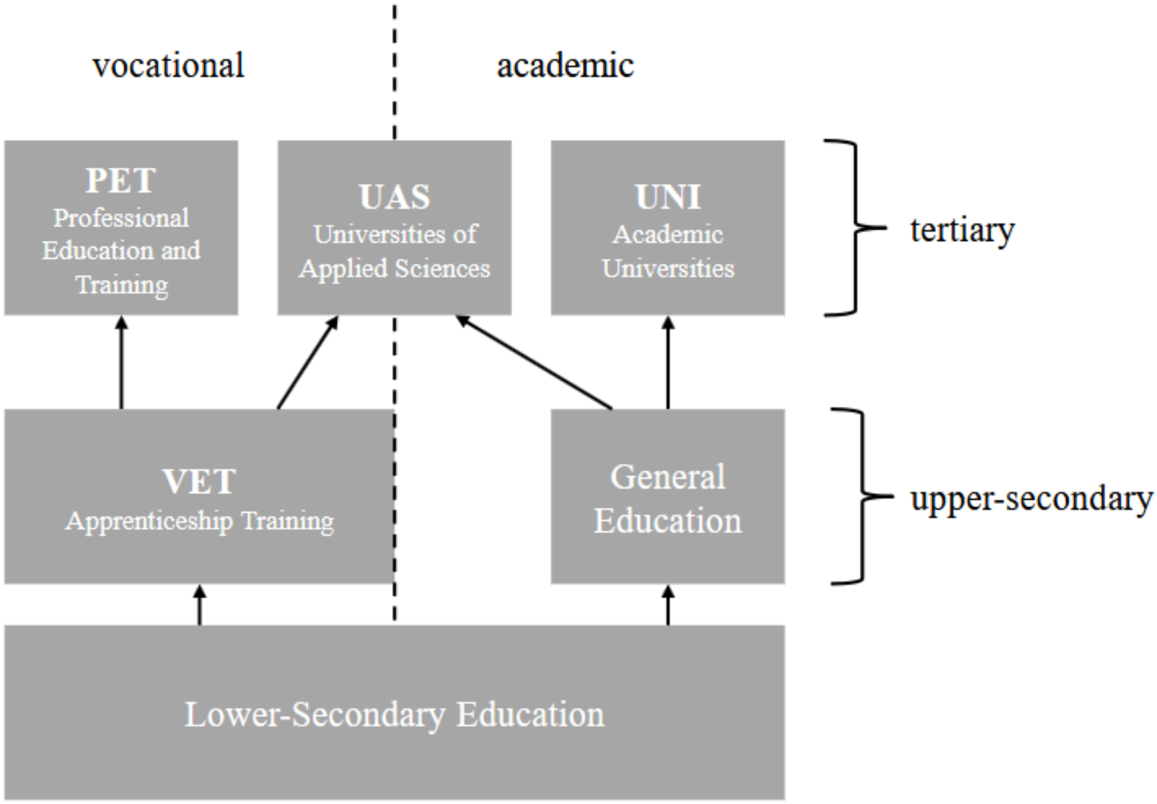
2.1. The Swiss education system: educational backgrounds in inventor teams

As our study investigates inventor teams in Switzerland, we first briefly describe the different types of educational backgrounds in the Swiss education system. We characterize the distinct skillset of each educational background, with an emphasis on the skills that contribute to inventor teams.

Figure 1 provides a simplified illustration of the main educational pathways in the Swiss education system. About two-thirds of Switzerland’s workforce initially choose vocational education and training (VET) at the upper-secondary level through apprenticeship programs, with one-third of them later proceeding to a tertiary-level education. Specifically, about 15% of the workforce complete advanced Professional Education and Training (PET) programs and about 16% obtain tertiary-level vocational degrees from Universities of Applied Sciences

(UAS). About 40% of these workers remain with an upper-secondary vocational degree as their highest
qualification (BFS, 2024a; BFS, 2024b).

Figure 1: *Main* p*athways in the* Swiss e*ducation* s*ystem*



Note: Simplified illustration of the Swiss education system. For a comprehensive depiction, see State Secretariat for Education, Research and Innovation (SERI, 2019).

Following the academic track, about 15% of the work-force acquire a tertiary-level degree from an academic university (SKBF, 2023). In our analysis of inventor teams we distinguish among four distinct types of education, each contributing unique skill sets to the joint innovation task:

- *VET* (vocational): Upper-secondary vocational education in Switzerland is obtained through recognized apprenticeship programs[3] and provides individuals with mid-level vocational skills. It equips its graduates with occupation-specific expertise, practical problem-solving skills, and hands-on technical proficiency. VET workers play a critical role in innovation processes, for example, in prototype construction

[3] About 95% of upper-secondary vocational qualifications in Switzerland are obtained through dual apprenticeship training, where apprentices typically spend about one-quarter of their education in vocational schools and three-quarters in firm-specific practical training at the workplace. However, as only 5% attend school-based vocational education, we use “VET” in this paper exclusively to refer to dual VET education.

or the practical implementation of ideas in laboratory settings.

- *PET* (vocational): Tertiary-level professional education is obtained through extensive workplace experience following apprenticeship training and advanced professional qualifications and training (e.g., master craftsmen and technicians). It equips graduates with high-level vocational skills and experience-based technical expertise. As a prerequisite for obtaining a *PET* degree, individuals must have previously acquired an upper-secondary-level *VET* degree and an occupation-specific duration of work experience.
- *UAS* (vocational): Universities of Applied Sciences offer tertiary-level education primarily to students with upper-secondary VET degrees, equipping graduates with a combination of vocational expertise and applied research knowledge. UASs award tertiary-level bachelor's and master's degrees at the same level as academic universities. Therefore, UAS graduates possess both vocational and applied research skills.
- *UNI* (academic): Academic universities offer tertiary-level academic education, equipping graduates with high-level academic skills, abstract reasoning skills, and fundamental research expertise. These skills are particularly valuable for tasks demanding scientific innovation and conceptual breakthroughs. About 80% of the academic university graduates are from a university ranked among the top 200 worldwide (SKBF, 2023), i.e., an academic education at the research frontier.

Backes-Gellner and Pfister (2019) illustrate in a qualitative study this division of roles in practice. In one of the studied firm's R&D department, only about 10% of employees hold a UNI degree, while roughly 90% have vocational backgrounds (VET, PET, or UAS). In developing components for the Mars Rover, UNI graduates in this department contributed conceptual design and scientific expertise, VET graduates focused on prototyping and practical implementation, PET graduates added advanced technical know-how from experience, and UAS graduates bridged between research and practice by translating workshop feedback into the design process. This example shows how innovations in complex projects emerge from the complementary interaction of diverse educational skill sets.

2.2. Vocational education, educational diversity, inventor teams, and innovation

To derive hypotheses on how the educational composition of inventor teams might affect their team performance we build on two strands of innovation literature. First, we build on the literature on the contribution of vocational education to innovation. This literature finds that Swiss firms that participate in apprenticeship training and integrate vocationally trained workers into their skill mix are more innovative than other firms (e.g., Meuer et al., 2015; Rupietta & Backes-Gellner, 2019). This increase in innovation is channeled through institutional factors such as the diffusion of new technologies through constant VET curriculum updates (e.g., Rupietta & Backes-Gellner, 2019; Schultheiss et al., 2024) and bidirectional knowledge spillovers between *UNI* and *VET* graduates (Backes-Gellner et al., 2017). These findings support the hypothesis that a complementary relationship between highly skilled academic R&D personnel and vocationally trained workers drives increased innovation outcomes.

Most recently, Matthies and Thomä (2025) use data from the German manufacturing sector to examine the innovation activities of workers with *VET* and *PET* educational backgrounds. They report that workers from both backgrounds contribute to firm-level innovation activities. However, whereas Matthies and Thomä (2025) rely on individual-level survey data, our study advances the literature by explicitly analyzing team-level complementarities between individuals with academic and vocational backgrounds.

Second, we build on the literature on the influence of educational diversity on team-level performance and firm-level innovation. This literature further supports the hypothesis that a mix of educational backgrounds, such as vocational and academic, improves innovation outcomes. Although not studying innovation performance, team-level studies demonstrate a positive influence of diversity in educational fields or levels on general team performance (e.g., Schubert and Tavassoli, 2020; Valls et al., 2016; Yang and Choi, 2024). These studies suggest that diversity across types of education is also positively associated with the performance of inventor teams. Furthermore, studies that analyze regional- and firm-level educational diversity find a positive effect on the likelihood of firms to innovate (Bolli et al., 2018; McGuirk & Jordan, 2012; Østergaard et al., 2011).

For example, using Swiss firm-level data, Bolli et al. (2018) analyze the effect of vertical educational diversity on innovation performance. They argue that diversity enhances the creative moment in the innovation phase and show that educational diversity significantly increases the extensive margin of R&D and product innovation in a firm. Given the high representation of vocational backgrounds in the Swiss workforce, these findings indicate an innovation-enhancing, complementary relationship between academic and vocational backgrounds.

Building on the literature that (a) analyzes the impact of vocationally educated workers on innovation; and (b) studies the relationship between educational diversity, team performance, and innovation activity, we anticipate a complementary relationship between academic and vocational backgrounds—a relationship that strengthens the innovation performance of inventor teams. We therefore propose the following hypothesis:

H1. Inventor teams with a mix of both vocational (*VET* or *PET*) and academic (*UNI*) educational backgrounds perform better than teams with only one type of educational background.

2.3. Universities of Applied Sciences and innovation

Additionally, our research builds on literature that analyzes the influence of UASs on innovation, which shows that UAS graduates foster innovation by combining tertiary-level vocational skills and applied research knowledge. For example, Lehnert et al. (2020) show that the establishment of UAS campuses in Switzerland led to a significant increase in the R&D spending and employment of regional firms. Their finding indicates that UAS graduates do not merely substitute for academically or vocationally trained workers but are hired as complements to the R&D workers already on the team. Similarly, Pfister et al. (2021) document a corresponding increase in patenting activities in regions surrounding those UAS campuses. Furthermore, qualitative case studies by Backes-Gellner & Pfister (2019) suggest that one mechanism underlying these effects is the bridging function of UAS graduates. By combining vocational skills with applied research knowledge, they facilitate collaboration and knowledge exchange between team members with vocational and academic backgrounds. However, while the studies analyze the influence of *UAS* graduates at the region and firm levels, our study is the first to investigate the specific role of *UAS* graduates within inventor teams.

Given these presented findings, we expect that *UAS* graduates likely act as bridge builders in inventor teams between the team members with distinctly different vocational and academic educational backgrounds. Without *UAS* graduates, those vocationally and academically trained workers would have only a marginal knowledge overlap. Thus, we formulate the following hypothesis:

H2: Inventor teams with both vocationally (*VET* or *PET*) and academically (*UNI*) educated members perform better when at least one member has a *UAS* educational background.

3. Data

3.1. Data sources

For the empirical analysis, we combine two data sources to measure the educational background of individual inventor team members and team performance. First, we use data from the European Patent Office's (EPO) Worldwide Patent Statistical Database (October 2023 version), which includes detailed information on applicants and inventors of patents filed at the EPO since 1980. Among other items, this information includes inventors' names, applicants' names,[4] inventors' and applicants' addresses, and common patent quality measures such as the patents' number of forward citations, the patent family size, and the patents' number of priority claims. We define all inventors listed on a patent as the inventor team. While innovation output can be captured along several dimensions (e.g., Bolli et al., 2018), patenting serves as a well-established and widely used indicator of high-level, radical innovation activity (e.g., Mason et al., 2020; Pfister et al., 2021).

Second, we match the EPO inventors to their LinkedIn profiles, thereby creating a novel dataset on inventors' educational backgrounds. The LinkedIn profiles contain detailed information such as names, educational degrees and the degree granting institutions, as well as current and previous employers and their locations. To match the LinkedIn information with the EPO information, we need to identify the same individual in each dataset based on the available qualitative information, such as inventor names and employer names. To do so, we develop an automated procedure that matches individuals by their full name and then verifies true matches using the employment history. We confirm name matches if LinkedIn profiles show employment at the patent applicant firm or institution.[5] Based on this matching procedure,

[4] For most patents, firms or institutions where the invention process takes place act as applicants. These applicants thus are likely the employers of the patent inventors.

[5] We apply a two-step matching decision rule. First, we match the data on the individuals' full names. Out of 567,829 Swiss inventors, we identified 213,646 unique inventors, with each inventor having on average 12.8 name matches. Given that LinkedIn launched only in the early 2000s and that the EPO data go back until 1980, thus containing many inventors who do not have LinkedIn profiles for the simple reason of not participating in the labor market anymore, we consider the name match rate of more than one-third as high. Second, to rule out false matches and to choose the true match in case of multiple exact name matches, we use the employment history in the individual biographies to decide whether the name match is false or true. If an individual was also employed by the firm/institution that acted as the patent applicant according to the individual's LinkedIn profile, we consider the name match true.

our sample of patent applicants with true LinkedIn matches consists of 31,501 inventors in Switzerland who filed at least one patent after 1980 and had a LinkedIn profile including educational information in 2024.[6] Thus, this dataset provides unique insights into the educational backgrounds of inventor teams.

3.2. Educational background classification

Based on the matched LinkedIn information, we identify the educational background of matched inventors from Switzerland. For each inventor we determine their educational background by selecting the most recently acquired formal, state-recognized degree listed in their LinkedIn profile. Using the four types of educational backgrounds that we characterize in Section 2.1, we apply the following classification strategy: First, we identify upper-secondary vocational education (*VET)* by recognized degree titles such as a "Polymechanic EFZ"—i.e., a degree in one of the more than 200 apprenticeship occupations in Switzerland.[7] Second, we identify tertiary-level professional education and training (*PET*) based on its distinct degree titles such as "Microtechnician HF", similar to upper-secondary-level *VET*.[8] Third, we identify degrees obtained from a UAS by the institution's name. Fourth, we identify academic education (*UNI)* obtained from an academic university by the university's name, including degrees earned from foreign universities and colleges.

Additionally, we define two supplementary categories that do not correspond to either vocational or academic educational backgrounds, which is uncommon but does occur in the Swiss education system. First, we classify general educational backgrounds, corresponding to individuals whose highest educational qualification is compulsory or general upper-secondary education (e.g., Matura).[9] Second, we classify all educational backgrounds that cannot be assigned to the categories *VET*, *PET*, *UAS*, *UNI*, or general education as unclassified. Reasons for an unclassified categorization are training from education institutions that lack state

[6] Of 42,113 matched inventors in Switzerland, 10,610 had LinkedIn profiles that either lacked education information or contained non-classifiable education information.
[7] Given that about three-quarters of the training time in dual VET programs take place in the training firm, we also identify VET degrees by analyzing the LinkedIn employment history of inventors.
[8] These tertiary-level professional education and training titles include specific job titles as well as degree titles such as 'Eidgenössischer Fachausweis,' 'Eidgenössisches Diplom,' 'Meister,' and 'Techniker".
[9] Typically, upper-secondary general education aims at preparing students for academic studies.

recognition,[10] unclassifiable foreign degrees, or missing information on LinkedIn profiles. Consequently, we treat inventors with an unclassified educational background as inventors for whom we could not identify a matching LinkedIn profile.

The distribution of educational backgrounds among patent holders notably differs from the overall Swiss workforce. While about 40% of the overall workforce holds VET as their highest qualification, and about 15% each hold PET, UAS or UNI degrees, inventors typically exhibit higher educational qualifications. In our sample of 31,501 matched inventors, about 3% hold an upper-secondary-level VET program (*VET*) as their highest qualification, about 3% hold a *PET* degree, about 14% hold a *UAS* degree, and about 75% hold an academic university degree (*UNI*). The remaining inventors either have compulsory or upper-secondary general education (approximately 2%) or are not classified (approximately 2%).

3.3. Patent quality measures

We measure inventor team performance through the quality of the patent(s) they jointly file. The EPO data provides several established patent quality indicators that capture the technological and economic value of patented inventions, including the patents' number of forward citations, the patent family size, and the patents' number of priority claims (for an overview of patent quality indicators, see Squicciarini et al., 2013). Each indicator captures different aspects of the patents' economic and technological value. For instance, the patents' number of forward citations is particularly relevant, as highly cited patents often serve as a foundation for subsequent innovations (Hall et al., 2005; Harhoff et al., 2003).[11] While our empirical analysis incorporates all three quality indicators, we use the patents' number of forward citations as our primary outcome, due to its well-established role as an innovation quality indicator in the literature that analyzes patenting activities (e.g., Cowan & Zinovyeva, 2013; Pfister et al., 2021).

4. Method

[10] If an inventor's most recently acquired degree falls into the private further education category, we examine their second most recent degree to determine if it is a formal qualification, continuing this process until a formal degree is identified.

[11] The patent family size indicates the geographical scope of protection, with larger families reflecting higher economic and technological value due to broader international coverage (Lanjouw et al., 1998; Harhoff et al., 2003). The number of claims defines the scope of the exclusive rights granted by a patent. A higher number of claims typically reflects greater breadth of the rights conferred by a patent (OECD, 2009) and the expected market value (Lanjouw & Schankerman, 2001; 2004).

4.1. Empirical framework

To empirically analyze these complementarities, we employ the supermodularity framework that Milgrom and Roberts (1990) originally introduced and Mohnen and Röller (2005) further developed. This framework is widely established in innovation research to examine complementarities among innovation factors (e.g., Ballot et al., 2015; Guisado-González et al., 2017; Serrano-Bedia et al., 2018) and across broader economic and management research domains (see Ennen & Richter, 2010). Compared to interaction terms in standard regression analyses, which become overly complex to interpret when multiple interactions are included, the supermodularity framework allows us to systematically assess the relationships between multiple factors. This advantage is particularly valuable given the numerous possible educational background combinations in inventor teams.

The application of this framework tests for complementarity by examining whether an inventor team performance function exhibits supermodularity or submodularity. Supermodularity is an "increasing returns" property: adding an educational background to a team that already has one type of background provides an at least as large performance increase as adding it to a team without that type (Fujishige, 2005). For example, for two educational backgrounds such as *VET* and *UNI,* an inventor team performance function $f(VET, UNI)$ has four possible combinations: $f(0,0)$, $f(1,0)$, $f(0,1)$, $f(1,1)$, representing the absence or presence of each educational background. According to Milgrom and Roberts (1990), strict supermodularity (i.e., complementarity) between *VET* and *UNI* holds if:

$$f(1,1) - f(0,1) > f(1,0) - f(0,0) \tag{1}$$

Intuitively, this condition implies that the marginal performance benefit of adding educational background *VET* to a team is higher when educational background *UNI* is already present, compared to when *UNI* is not present. Conversely, submodularity (substitutability) implies that the marginal performance benefit of adding educational background *VET* to a team is lower when educational background *UNI* is already present, compared to when *UNI* is not present. If neither super- nor submodularity significantly holds (i.e., the marginal effect of one educational background does not differ significantly dependent on the presence of the other), the educational backgrounds have no relation. Thus, the educational backgrounds are neither complements nor substitutes.

In reality, inventor teams often feature more than two educational backgrounds. Therefore, we adapt an empirical approach from the innovation literature (Ballot et al., 2015; Guisado-Gonzalez et al., 2017; Serrano-Bedia et al., 2018) by applying conditional complementarity tests. To do so, we evaluate how complementarities between two educational backgrounds depend on the presence or absence of additional backgrounds (e.g., *UAS*, *PET*). Compared to unconditional complementarity tests, which evaluate complementary effects without considering additional context or variables and therefore often yield inconclusive results (Ballot et al., 2015), conditional complementarity tests allow for a more nuanced understanding of interactions between multiple factors. Possible outcomes of these tests include strict complementarity (consistent complementarity across conditions), conditional complementarity (complementary dependent on conditions), strict and conditional substitutability (consistent substitutability across conditions, and substitutability dependent on conditions). Further possible outcomes are no relationship (if no condition detects any relationship), or inconclusive results (if some conditions indicate complementarity while others indicate substitutability).

4.2. Sample composition

For our analysis, we exclude single-inventor patents since our interest lies specifically in team-level complementarities.[12] Additionally, we restrict the sample to inventor teams in which the educational backgrounds of at least 50% of the team members are successfully classified, excluding 57,588 inventor teams from the sample but ensuring robust and reliable measures of team composition. To validate that our sample adequately represents the broader population of Swiss patenting teams, we compare both samples along several dimensions. Table 1 presents the distribution of patent technology fields and team sizes (measured by the total number of inventors listed on each patent) for (a) the patents filed at the EPO since 1980 with at least 50% Swiss-based inventors (reflecting our sample restriction that at least 50% of team members must be successfully classified) and (b) the patents included in our matched sample. The similarity in distribution of technology fields and team sizes between both groups confirms the representativeness of our matched inventor team sample.

Similarly, Table 2 shows the yearly distribution of patents in the two samples. Patents from 2010–2020 are slightly overrepresented in the matched sample. This pattern is not surprising, as inventors active in more recent years are more likely to maintain a LinkedIn

[12] By this, 19,019 single inventor patents are excluded from the analysis.

profile today, which increases the probability of successfully matching their educational information. However, this skewness toward more recent years is an expected feature of the underlying data and reflects the higher likelihood of more recently active inventors having LinkedIn profiles, rather than a systematic bias in the matching procedure.

Table 1: *Frequency of team sizes in the Swiss base sample of inventor teams and in the Swiss matched inventor teams sample*

Technological area	Base sample *Frequency (%)*	Matched sample *Frequency (%)*	Team size	Base sample *Frequency (%)*	Matched sample *Frequency (%)*
OrganicChem	33943 (10.62)	3192 (9.13)	2	149568 (46.12)	20494 (57.69)
Pharmaceuticals	25360 (7.93)	2601 (7.44)	3	78032 (24.06)	6085 (17.13)
Measurement	24605 (7.7)	3228 (9.23)	4	48779 (15.04)	5919 (16.66)
MedicalTechn	23535 (7.36)	3143 (8.99)	5	21154 (6.52)	1275 (3.59)
Biotechnology	14466 (4.53)	1859 (5.32)	6	12276 (3.79)	1042 (2.93)
Handling	13661 (4.27)	903 (2.58)	7	5915 (1.82)	282 (0.79)
Electr/Energy	13577 (4.25)	1596 (4.56)	8	3625 (1.12)	299 (0.84)
MaterialsChemistry	13056 (4.08)	1600 (4.58)	9	1718 (0.53)	44 (0.12)
FoodChemistry	10809 (3.38)	849 (2.43)	10	1311 (0.4)	51 (0.14)
OthConsGoods	10707 (3.35)	1215 (3.47)	11	642 (0.2)	21 (0.06)
ComputerTech	10309 (3.23)	1352 (3.87)	12	498 (0.15)	8 (0.02)
Textiles/PaperMachines	10068 (3.15)	785 (2.24)	13	263 (0.08)	0
MachineTools	9147 (2.86)	856 (2.45)	14	165 (0.05)	3 (0.01)
ChemEngineering	8929 (2.79)	1162 (3.32)	15	146 (0.05)	0
Polymers	8028 (2.51)	726 (2.08)	16	72 (0.02)	0
OtherMachines	7997 (2.5)	859 (2.46)	17	60 (0.02)	0
FurnitureGames	7385 (2.31)	525 (1.5)	18	45 (0.01)	2 (0.01)
Engines/Pumps/Turbines	6963 (2.18)	713 (2.04)	19	24 (0.01)	0
Materials/Metallurgy	6571 (2.06)	726 (2.08)	20	5 (0)	0
CivilEngineering	6565 (2.05)	536 (1.53)	21	5 (0)	0
SurfaceTechn	5839 (1.83)	473 (1.35)	22	5 (0)	0
MechElements	5406 (1.69)	474 (1.36)	23	0 (0)	0
Transport	5254 (1.64)	599 (1.71)	24	0 (0)	0
Optics	5232 (1.64)	580 (1.66)	25	2 (0)	0
Audiovisual	4777 (1.49)	740 (2.12)	26	1 (0)	0
Telecom	4474 (1.4)	623 (1.78)			
Control	4135 (1.29)	530 (1.52)			
Semiconductors	3983 (1.25)	636 (1.82)			
ThermProcesses	3563 (1.11)	439 (1.26)			
DigitalComm	3049 (0.95)	336 (0.96)			
AnalysisBioMaterials	2421 (0.76)	284 (0.81)			
EnvironmentalTechn	2342 (0.73)	363 (1.04)			
IT_Methods	1665 (0.52)	222 (0.63)			
BasicCommProcess	1525 (0.48)	201 (0.57)			
MicroStrucNano	292 (0.09)	42 (0.12)			
Total	319638 (100)	34968 (100)	**Total**	324311 (100)	35486 (100)

Table 2: *Frequency of filed patents per year in the Swiss base sample of inventor teams and in the Swiss matched inventor teams sample*

	Base sample	**Matched sample**
Year	*Frequency (%)*	*Frequency (%)*
1980	1675 (0.52)	11 (0.03)
1981	1779 (0.55)	25 (0.07)
1982	1706 (0.53)	31 (0.09)
1983	1719 (0.53)	15 (0.04)
1984	2089 (0.64)	29 (0.08)
1985	2385 (0.74)	15 (0.04)
1986	2880 (0.89)	39 (0.11)
1987	3279 (1.01)	57 (0.16)
1988	3436 (1.06)	79 (0.22)
1989	4354 (1.34)	94 (0.26)
1990	4011 (1.24)	148 (0.42)
1991	4210 (1.30)	157 (0.44)
1992	4896 (1.51)	235 (0.66)
1993	5146 (1.59)	196 (0.55)
1994	5953 (1.84)	235 (0.66)
1995	6024 (1.86)	225 (0.63)
1996	7095 (2.19)	290 (0.82)
1997	7170 (2.21)	416 (1.17)
1998	7894 (2.43)	611 (1.72)
1999	8897 (2.74)	709 (2.00)
2000	9571 (2.95)	772 (2.18)
2001	9328 (2.88)	944 (2.66)
2002	9196 (2.84)	856 (2.41)
2003	10222 (3.15)	1054 (2.97)
2004	10585 (3.26)	1213 (3.42)
2005	11290 (3.48)	1288 (3.63)
2006	10869 (3.35)	1284 (3.62)
2007	11660 (3.60)	1335 (3.76)
2008	10604 (3.27)	1408 (3.97)
2009	10973 (3.38)	1324 (3.73)
2010	11577 (3.57)	1608 (4.53)
2011	12076 (3.72)	1475 (4.16)
2012	13417 (4.14)	1718 (4.84)
2013	11841 (3.65)	1736 (4.89)
2014	11979 (3.69)	1765 (4.97)
2015	11844 (3.65)	1832 (5.16)
2016	11875 (3.66)	1903 (5.36)
2017	11457 (3.53)	1848 (5.21)
2018	11439 (3.53)	1923 (5.42)
2019	10944 (3.37)	1832 (5.16)
2020	9160 (2.82)	1581 (4.46)
2021	5569 (1.72)	1116 (3.14)
Total	324285 (100)	35486 (100)

4.3. Regression specification

To perform the complementarity analysis, we first create an inventor team performance function to consistently estimate the effects of educational backgrounds on inventor team performance via OLS. Our dependent variable *Q* represents our measures for team performance, i.e., the quality of patent *i* (the patents' number of forward citations in our main specification, as well as patent family size and patents' number of priority claims in additional specifications).[13] We construct 16 dummy variables (Xi_k with $k = 1, \ldots, 16$) as input variables that represent each possible combination of the four educational backgrounds (*VET*, *PET*, *UAS*, and *UNI*). For example, the dummy variable for the team performance function *f*(1,0,0,1) represents teams with *VET* and *UNI* educational backgrounds but without *PET* and *UAS* educational backgrounds. The dummy variable representing teams in which all four educational backgrounds are absent *f*(0,0,0,0), includes only inventors that are classified with general educational backgrounds, i.e., compulsory or upper-secondary general education. Additionally, the regression contains a vector of control variables *Z*, including the patent application year (according to the priority filing date), the inventor team size, the technology field of the patent, the share of inventors with unclassified educational backgrounds, and the share of inventors from abroad. ϵ denotes the error term:

$$Q_i = \sum_{k=1}^{16} \beta_k X_{ik} + \gamma Z_i + \epsilon_i \tag{2}$$

Finally, we use the estimated regression coefficients to evaluate conditional complementarities between educational backgrounds, as stated in our two hypotheses. More specifically, we test for pairwise complementarities between academic (*UNI)* and vocational backgrounds (*VET* or *PET*), in which the complementarity is conditional on the absence of additional educational backgrounds. By doing so, we investigate whether combining academic and vocational education enhances inventor team performance compared to inventor teams with only one type of background present (hypothesis 1).

Furthermore, we test whether adding *UAS* graduates to teams composed of academic

[13] We applied the inverse hyperbolic sine (IHS) transformation to the outcome variable prior to regression analysis to account for their concentration around zero, the presence of zeros, and to address the presence of a few larger values in a statistically robust manner without distorting the overall distribution.

(*UNI*) and vocational (*VET* or *PET*) backgrounds further increases team performance, i.e., whether UAS graduates serve as bridge builders (hypothesis 2). Given the inequality constraint (1), the inventor team performance function $f(VET,PET,UAS,UNI)$, and our two hypotheses, the empirical conditions to test complementarities between *UNI* and *VET,* as well as *UNI* and *PET,* are as follows:

Figure 2: *Supermodularity-based conditions for testing complementarity between academic (UNI) and vocational (VET, PET) educational backgrounds, with and without UAS presence*

	H1 *UAS* not present	**H2** *UAS* present
VET-UNI	$f(1,0,0,1) + f(0,0,0,0) - f(1,0,0,0) - f(0,0,0,1) = 0$ Complementarity if: $f(1,0,0,1) + f(0,0,0,0) - f(1,0,0,0) - f(0,0,0,1) > 0$	$f(1,0,1,1) + f(0,0,1,0) - f(1,0,1,0) - f(0,0,1,1) = 0$ Complementarity if: $f(1,0,1,1) + f(0,0,1,0) - f(1,0,1,0) - f(0,0,1,1) > 0$
PET-UNI	$f(0,1,0,1) + f(0,0,0,0) - f(0,1,0,0) - f(0,0,0,1) = 0$ Complementarity if: $f(0,1,0,1) + f(0,0,0,0) - f(0,1,0,0) - f(0,0,0,1) > 0$	$f(0,1,1,1) + f(0,0,1,0) - f(0,1,1,0) - f(0,0,1,1) = 0$ Complementarity if: $f(0,1,1,1) + f(0,0,1,0) - f(0,1,1,0) - f(0,0,1,1) > 0$

Following Guisado-Gonzales et al. (2017) and Serrano-Bedia et al. (2018), the conditional complementary analysis involves two steps. First, we test for the existence of a statistically significant relationship between the educational backgrounds specified in Hypotheses 1 and 2, i.e., *UNI* combined with *VET* or *PET,* conditional on *UAS* presence or absence. Second, if the relationship is statistically significant, we determine whether it is complementary or substitutive. We systematically apply our two-step approach to all relevant combinations of educational backgrounds and across each patent quality measure.

5. Results

5.1. Descriptive analysis: inventor team composition and patent quality

Table 3 shows the frequency and average patent quality associated with each combination of educational backgrounds within inventor teams. Our dataset includes 35,486 inventor teams, each containing at least one matched inventor from Switzerland. Most inventor teams exhibit homogeneous educational background compositions, i.e., all inventor team members have the same educational background type. Specifically, the most frequent group comprises teams with only UNI educational backgrounds (77.91%). The second most frequent group comprises teams with only UAS educational backgrounds (7.90%). Teams with only VET backgrounds constitute 2.29% and teams with only PET backgrounds 2.58% of the sample. Among inventor teams with two educational backgrounds, combinations involving UNI backgrounds exhibit the highest frequencies. The most common combination is UNI and UAS (4.74%), followed by UNI and VET (2.78%), and UNI and PET (1.05%). Teams combining three educational backgrounds are least common. The most frequent combination in this category is UNI, UAS, and VET (0.58%), followed by UNI, PET, and UAS (0.17%), UAS, PET and VET (0.03%), and UNI, PET and VET (0.01%). Notably, we observe only one single inventor team in our dataset that includes all four educational backgrounds.

Regarding patent quality, within the group of inventor teams with one type of educational background, teams composed exclusively of the *UNI* educational background exhibit the highest average patent quality across all three quality indicators, followed by teams composed exclusively of the *VET* background. Among teams with two backgrounds, the combination of *UNI* and *VET* clearly shows the highest average patent quality across all indicators, surpassing the average patent quality of teams with only one type of educational background. Teams that combine *UNI*, *UAS*, and *VET* backgrounds display remarkably high patent quality, particularly in our primary quality indicator (number of forward citations), significantly outperforming all other educational combinations. For the other two indicators—number of priority claims and patent family size—the *UNI* and *VET* combination remains the top-performing team composition, closely followed by the *UNI*, *UAS*, and *VET* combination. Therefore, the descriptive evidence fits the relationships we state in our hypotheses, indicating complementarities particularly between *UNI* and *VET* educational backgrounds, and further enhanced patent quality when complemented by the *UAS* background. However, the descriptive analysis does not suggest strong complementarities between *UNI* and *PET* backgrounds.

Table 3: *Frequency and average patent quality of educational background team compositions*

Education Combination	Frequency (%)	Avg. Forward Citations	Avg. Priority Claims	Avg. Family Size
All absent (0,0,0,0)	431 (0.76)	0.63	0.91	8.16
One Educational Background Present				
VET only (1,0,0,0)	818 (2.29)	0.72	0.93	12.40
PET only (0,1,0,0)	1,080 (2.58)	1.98	0.86	8.09
UAS only (0,0,1,0)	4,312 (7.90)	0.66	0.81	8.19
UNI only (0,0,0,1)	25,565 (77.91)	1.09	0.99	13.72
Two Educational Backgrounds Present				
VET & UNI (1,0,0,1)	599 (2.78)	1.66	1.30	21.42
PET & UNI (0,1,0,1)	402 (1.05)	1.05	0.82	7.63
UAS & UNI (0,0,1,1)	1,887 (4.74)	0.90	0.91	9.99
VET & UAS (1,0,1,0)	73 (0.17)	0.83	0.81	8.60
VET & PET (1,0,1,0)	34 (0.02)	0.18	0.62	5.18
PET & UAS (0,1,1,0)	194 (0.26)	0.48	0.85	6.57
Three Educational Backgrounds Present				
VET & UAS & UNI (1,0,1,1)	32 (0.58)	6.47	1.38	22.06
PET & UAS & UNI (0,1,1,1)	45 (0.17)	1.33	0.91	8.27
VET & PET & UNI (1,1,0,1)	4 (0.01)	0.25	0.75	2.25
VET & PET & UAS (1,1,1,0)	11 (0.03)	0.91	0.91	7.09
All Educational Backgrounds Present				
VET & PET & UAS & UNI (1,1,1,1)	1	0	0.00	2.00
Total	35,486 (100)	1.01	0.96	12.58

5.2. Complementarity analysis using the supermodularity framework

Table 4 summarizes the results of our complementarity analysis using the supermodularity framework (Appendix table A1 provides the detailed OLS regression results). We first tackle our main patent quality indicator, the patents' number of forward citations. For Hypothesis 1, stating that complementary effects arise between academic (*UNI*) and vocational backgrounds (*VET* and *PET*), our result shows no direct complementary relationship between *UNI* and *VET* in the absence of *UAS* graduates. Similarly, the results indicate no complementary relationship between *UNI* and *PET* in the absence of *UAS* graduates. Thus, we find no support for Hypothesis 1 regarding the patents' number of forward citations when patents are generated by teams that include only UNI and either VET or PET backgrounds, without any UAS graduates. However, consistent with our hypothesis 2 that *UAS* graduates act as bridge builders, we find strong complementarities between *UNI* and *VET,* as well as between *UNI* and *PET* backgrounds, when the *UAS* background is present in the inventor team. This finding indicates that *UAS* graduates facilitate collaboration and knowledge exchange between academically and vocationally educated team members, thus enhancing their performance as measured by the number of forward citations.

Table 4: *Results of the* s*upermodularity* a*nalysis –matched* s*ample*

	H1 UAS not present			**H2** UAS present		
	Forward Citations	*Priority Claims*	*Family Size*	*Forward Citations*	*Priority Claims*	*Family Size*
VET-UNI	No Relation	**Complements**	No Relation	**Complements**	**Complements**	**Complements**
PET-UNI	No Relation	**Substitutes**	**Substitutes**	**Complements**	No Relation	No Relation

Turning to the additional patent quality indicators, our findings provide support for Hypothesis 1, i.e., the complementarity between *UNI* and *VET* backgrounds. For both priority claims and patent family size we find evidence of complementarity, even in the absence of *UAS* graduates. This finding suggests that a complementarity between *UNI* and *VET* backgrounds exists, although not for all patent quality measures. We also find support for Hypothesis 2 that *UAS* graduates serve as bridge builders between *UNI* and *VET* backgrounds with priority claims as patent quality indicator.

For *UNI* and *PET* backgrounds, however, we do not find complementarities for the two additional patent quality measures, independent of the presence of *UAS* graduates. On the contrary, our results even indicate a substitution effect between UNI and PET backgrounds if the UAS background is not present for patent quality as measured by priority claims.

In summary, we find consistent evidence for a complementary relationship between *UNI* and *VET* backgrounds, which is further enhanced when the *UAS* background is present as well. Therefore, our findings clearly show that UAS graduates can serve as bridge builders between academically and vocationally educated workers. For *UNI-PET* combinations, we do not find any conclusive evidence for a complementary relationship. Our findings strengthen the argument that combining academic and vocational skills, particularly upper-secondary *VET*, can enhance the performance of inventor teams.

5.3. Robustness of the complementarity analysis

To test whether outliers in patent quality drive our results, we re-estimate the OLS and complementarity analyses after trimming the top and bottom 10% of observations within each educational team composition category (see Appendix Tables A2 and A3). The results remain qualitatively unchanged and, if anything, become even stronger. In particular, the complementarity between *UNI* and *VET* backgrounds emerges more clearly, as we find a significant complementary relationship for all patent quality measures even in the absence of *UAS* graduates. This result indicates that the observed complementarities are not driven by outliers, but instead reflect a consistent premium from combining academic and vocational educational backgrounds.

To focus on more recent patenting, we re-estimated all models using only patents filed since 2000. The results (see Appendix Tables A4 and A5) mirror our baseline: *UNI* and *VET* remain complementary, visible without *UAS* and stronger when *UAS* members are part of a team. Patterns for *UNI* and *PET* stay mixed, with no robust complementarity in the post-2000 sample. Alternatively looking at the 1990–2010 period leads to the same conclusions. Together, these checks show that our findings are not tied to a specific period but hold across alternative time frames.[14]

6. Further analysis

To examine whether the identified complementarities between educational backgrounds vary across technological contexts, we conducted additional analyses for the 15 most frequent technology fields. These technology fields include *Organic Chemistry*, *Pharmaceuticals*, *Measurement*, *Medical Technology*, *Biotechnology*, *Materials Chemistry*, *Electrical/Energy*, *Computer Technology*, *Consumer Goods*, *Chemical Engineering*, *Handling*, *Food Chemistry*, *Other Machines*, *Machine Tools*, and *Polymers*. The analysis of different technology fields (summarized in Table 5) reveals considerable heterogeneity in the relationships between educational backgrounds, emphasizing that complementarities between academic (*UNI*) and vocational backgrounds (*VET* or *PET*) vary substantially depending on technological context.

[14] Results available upon request.

Table 5: *Results of the supermodularity analysis – technology areas*

	H1			H2		
	UAS not present			UAS present		
	Forward Citations	*Priority Claims*	*Family Size*	*Forward Citations*	*Priority Claims*	*Family Size*
OrganicChem *(n = 3,192)*						
VET-UNI	**Substitutes**	No Relation	No Relation	-	-	-
PET-UNI	No Relation	**Substitutes**	**Substitutes**	-	-	-
Pharmaceuticals (*n*=2,601)						
VET-UNI	No Relation	No Relation	**Substitutes**	-	-	-
PET-UNI	No Relation	**Substitutes**	**Substitutes**	-	-	-
Measurement (*n* = 3,228)						
VET-UNI	**Substitutes**	**Complements**	No Relation	**Substitutes**	No Relation	No Relation
PET-UNI	**Substitutes**	No Relation	No Relation	No Relation	No Relation	No Relation
Medical Technology (*n* = 3,143)						
VET-UNI	No Relation	No Relation	No Relation	**Complements**	No Relation	No Relation
PET-UNI	No Relation	**Substitutes**	No Relation	**Complements**	No Relation	No Relation
BioTechnology *(n = 1,859)*						
VET-UNI	No Relation	No Relation	No Relation	**Substitutes**	**Complements**	**Complements**
PET-UNI	No Relation	No Relation	No Relation	-	-	-
Materials Chemistry *(n = 1,600)*						
VET-UNI	No Relation	No Relation	No Relation	-	**Complements**	**Complements**
PET-UNI	No Relation	**Substitutes**	No Relation	-	-	-
Electr/Energy *(n = 1,595)*						
VET-UNI	No Relation	No Relation	No Relation	No Relation	No Relation	**Complements**
PET-UNI	No Relation	No Relation	No Relation	-	**Complements**	No Relation
ComputerTechnology *(n = 1,351)*						
VET-UNI	No Relation	No Relation	No Relation	-	-	-
PET-UNI	No Relation	No Relation	No Relation	**Complements**	**Complements**	**Complements**
OtherConsumerGoods *(n = 1,212)*						
VET-UNI	No Relation	No Relation	No Relation	**Substitutes**	No Relation	**Substitutes**
PET-UNI	No Relation	No Relation	No Relation	-	-	-
ChemEngineering *(n = 1,162)*						
VET-UNI	**Complements**	No Relation	No Relation	-	-	-
PET-UNI	**Complements**	No Relation	No Relation	-	-	-
Handling *(n = 903)*						
VET-UNI	**Substitutes**	No Relation	No Relation	-	-	-
PET-UNI	**Substitutes**	No Relation	No Relation	-	-	-
FoodChemistry *(n =850)*						
VET-UNI	-	-	-	-	-	-
PET-UNI	No Relation	No Relation	**Substitutes**	-	-	-
OtherMachines *(n=859)*						
VET-UNI	**Substitutes**	No Relation	No Relation	-	-	-
PET-UNI	No Relation	No Relation	No Relation	**Complements**	No Relation	No Relation
MachineTools *(n = 859)*						
VET-UNI	**Substitutes**	No Relation	No Relation	-	-	-
PET-UNI	**Substitutes**	No Relation	No Relation	**Substitutes**	No Relation	No Relation
Polymers *(n = 726)*						
VET-UNI	**Complements**	**Complements**	No Relation	**Complements**	**Complements**	**Complements**
PET-UNI	No Relation	**Substitutes**	**Substitutes**	-	-	-

For Hypothesis 1, which states that complementary effects between academic (*UNI*) and vocational backgrounds (*VET* and *PET*) arise in the absence of *UAS* graduates, our analysis identifies a complementary relationship in *Chemical Engineering* between *UNI* and both *VET* and *PET* backgrounds. In the technological field of *Polymers*, complementarity emerges only between *UNI* and *VET*, whereas the combination of *UNI* and *PET* exhibits substitutive effects.

Furthermore, we observe substitutive effects between vocational and academic backgrounds in *Organic Chemistry, Pharmaceuticals, Material Chemistry, Handling, Food Chemistry, Machine Tools*, and *Other Machines*. These findings suggest that inventor teams comprising exclusively vocational or academic backgrounds achieve higher patent quality in these technological fields than teams combining both backgrounds. In *Medical Technology, Biotechnology, Electrical/Energy, Computer Technology*, and *Consumer Goods*, we find either no relationship or inconclusive results.

Hypothesis 2 proposes that *UAS* graduates serve as bridge builders. Our analysis supports this hypothesis by revealing complementary effects between vocational and academic backgrounds in *Medical Technology, Materials Chemistry, Electrical/Energy, Computer Technology, Other Machines*, and *Polymers*, specifically when *UAS* graduates are part of the inventor team. The presence of *UAS* graduates increases complementarity between vocational and academic backgrounds across a broader range of technological fields, strengthening the argument that their combination of vocational expertise and applied research capabilities facilitates collaboration and knowledge exchange within teams. However, our results also indicate substitutive effects between vocational and academic backgrounds in *Measurement, Consumer Goods*, and *Machine Tools*, even when *UAS* graduates are present. Finally, in the technological fields of *Organic Chemistry, Pharmaceuticals, Biotechnology, Chemical Engineering, Handling*, and *Food Chemistry*, our analysis yields either inconclusive results, no relationship, or insufficient observations of specific educational background combinations to reliably assess supermodularity.

In summary, our further analyses indicate that the complementarities between educational backgrounds in innovation teams vary considerably by technological context, highlighting the context-dependent nature of these complementarities. Certain sectors, such as *Computer Technology, Electrical/Energy,* and *Chemical Engineering,* benefit significantly from combining vocational and academic skills, especially facilitated by *UAS* graduates to bridge vocational and academic skills. For example, *Electrical Energy* requires hands-on skills and practical experience for prototyping or mechanism reliability. Here, the practical skills provided by *VET* graduates complement the theoretical expertise of *UNI* graduates, enhancing innovation outcomes. In contrast, other sectors experience predominantly substitutive interactions, e.g. *Organic Chemistry*, reflecting limited added value from vocational-academic educational combinations. In *Organic Chemistry*, where innovation often focuses on broader synthetic methods or reaction processes, success relies less on precise execution and practical lab work and more on conceptual novelty. As a result, the combination of *UNI* and *VET* backgrounds does not provide a significant advantage. Understanding these context-specific dynamics is crucial for optimizing educational diversity in innovation teams and provides valuable insights for policymakers and firm management striving to enhance innovation performance.

7. Conclusion

This study provides evidence of complementary effects between vocational and academic educational backgrounds in inventor teams on team performance, measured by patent quality indicators. We find complementary relationships between university and upper-secondary vocational education, particularly when *UAS* graduates are also present in the team. This finding highlights the importance of integrating different knowledge sets—such as theoretical expertise and applied research skills—while ensuring sufficient overlap to enable effective collaboration and knowledge exchange. We find *UAS* graduates to act as bridge builders, encouraging communication and cooperation between academic and vocationally trained inventors. For example, in fields like *Medical Technology, Electrical/Energy,* and *Computer Technology,* where both theoretical expertise and applied skills are essential, the presence of *UAS* graduates enables teams to successfully integrate academic and vocational knowledge, leading to enhanced innovation outcomes.

Further analysis highlights the context-dependent nature of these complementarities across different technology fields. Certain sectors such as *Computer Technology, Electrical/Energy,* and *Chemical Engineering* benefit significantly from combining vocational and academic skills. However, other sectors such as *Organic Chemistry* experience predominantly substitutive interactions, thus showing limited added value from vocational-academic educational combinations. Therefore, these findings reflect the interdisciplinary and applied nature of certain fields.

Our results emphasize the importance of effectively combining different types of education in inventor teams to enhance innovation performance, depending on the field of innovation. Educational policymakers should take into consideration that a focus on academic education may miss out on the contributions of vocational education to innovation. For countries like Switzerland, where the majority of the workforce has a vocational education background, our findings highlight the value of maintaining a balanced educational landscape. Likewise, education policies should aim to strengthen pathways that integrate vocational and academic training, such as UASs, which play a critical role in bridging gaps between different types of skills. Therefore, to maintain their role as bridge builders between vocational and academic education, *UASs* must preserve their unique function of connecting theoretical knowledge with practical skills instead of evolving towards traditional universities.

While our study provides valuable insights, it has certain limitations. First, our data consists of inventors in patenting teams, leaving the role of vocational education in non-patent innovation fields, such as software development, unexplored. Future studies could expand this analysis to industries where other metrics than patents better capture innovation outcomes. Second, while our analysis covers key educational backgrounds of Swiss inventors, future research could investigate potential complementarities with foreign educational backgrounds. Additionally, future research could explore the underlying mechanisms of the complementarities in greater detail. For example, studying how team dynamics, task allocation and communication processes vary across technology fields could reveal insights into why complementarities are more pronounced in some contexts than in others.

Our study challenges the traditional emphasis on academic education as the main driver of innovation. We highlight how vocational education systems, like Switzerland's dual VET model, complement academic education to foster high-performing innovation teams. These findings offer valuable insights for both policymakers and firms to improve national and organizational innovation systems in a competitive global economy.

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Appendix

Table A1: *OLS-Regressions of the full matched sample for the patent quality indicators*

OLS Regression	**Forward Citations**	**Priority Claims**	**Patent Family Size**
All absent (0,0,0,0)	0.2137683	0.7796712***	2.781234***
UNI only (1,0,0,0)	0.2972121	0.7891067***	2.922142***
VET only (0,1,0,0)	0.1884903	0.7534296***	2.932047***
UAS only (0,0,1,0)	0.229947	0.761742***	2.845712***
PET only (0,0,0,1)	0.2082818	0.7856658***	2.720621***
UNI & VET (1,1,0,0)	0.3497609	0.8874338***	3.31416***
UNI & UAS (1,0,1,0)	0.2240031	0.7710457***	2.862963***
UNI & PET (1,0,0,1)	0.2347978	0.6826132***	2.694311***
VET & UAS (0,1,1,0)	0.2212135	0.7609702***	2.899532***
VET & PET (0,1,0,1)	-0.0666574	0.6162936***	2.585139***
UAS & PET (0,0,1,1)	0.080926	0.7509133***	2.661543***
UNI & VET & UAS (1,1,1,0)	1.233588**	1.019826***	3.292353***
UNI & VET & PET (1,1,0,1)	0.209597	0.7084202**	2.283025***
UNI & UAS & PET (1,0,1,1)	0.438785	0.7350096***	2.592399***
VET & UAS & PET (0,1,1,1)	0.6566253*	0.8766223***	3.050877***
UNI & VET & UAS & PET (1,1,1,1)	-0.5739278*	0.0273958	1.618784***
Technology Area Dummies	YES	YES	YES
Team Size Dummies	YES	YES	YES
Priority Year Dummies	YES	YES	YES
R-squared	0.4448	0.7804	0.9389
N	34,932	34,932	34,932

Note: The dependent variables are the IHS transformed number of forward citations, number of priority claims, and patent family size.
*Significance levels: $p < 0.1$ = *, $p < 0.05$ = **, $p < 0.01$ = ****
Standard errors are clustered at the inventor team level

Table A2: *Sensitivity Analysis: OLS Regressions of the Matched Sample (Excluding Top and Bottom 10% of Patent Quality per Team Composition)*

OLS Regression	**Forward Citations**	**Priority Claims**	**Patent Family Size**
All absent (0,0,0,0)	0.3627001	0.6544946***	2.856697***
UNI only (1,0,0,0)	0.3677819	0.7063929***	3.034923***
VET only (0,1,0,0)	0.3250789	0.6771101***	3.019676***
UAS only (0,0,1,0)	0.2825922	0.6377522***	2.812551***
PET only (0,0,0,1)	0.2736714	0.6572948***	2.710092***
UNI & VET (1,1,0,0)	0.4907539	0.816254***	3.532891***
UNI & UAS (1,0,1,0)	0.3508912	0.7078404***	2.886782***
UNI & PET (1,0,0,1)	0.3444818	0.5532267***	2.77665***
VET & UAS (0,1,1,0)	0.302509	0.6307201***	2.872558***
VET & PET (0,1,0,1)	0.0717303	0.4898707***	2.429091***
UAS & PET (0,0,1,1)	0.2510687	0.6889416***	2.692687***
UNI & VET & UAS (1,1,1,0)	1.012824**	1.009243***	3.541332***
UNI & VET & PET (1,1,0,1)	0.3780027	0.6444045***	2.247631***
UNI & UAS & PET (1,0,1,1)	0.6750073**	0.6151573***	2.667351***
VET & UAS & PET (0,1,1,1)	0.8095704**	0.8818282***	3.043374***
UNI & VET & UAS & PET (1,1,1,1)	-0.2150039	-0.0218369	-
Technology Area Dummies	YES	YES	YES
Team Size Dummies	YES	YES	YES
Priority Year Dummies	YES	YES	YES
R-squared	0.4043	0.7952	0.9748
N	32,181	33,791	26,571

Note: The dependent variables are the IHS transformed number of forward citations, number of priority claims, and patent family size.
*Significance levels: $p < 0.1$ = *, $p < 0.05$ = **, $p < 0.01$ = ****
Standard errors are clustered at the inventor team level

Table A3: *Sensitivity Analysis: Supermodularity Results with Reduced Sample (Excluding Top and Bottom 10% of Patent Quality per Team Composition)*

	H1 UAS not present			**H2** UAS present		
	Forward Citations	*Priority Claims*	*Family Size*	*Forward Citations*	*Priority Claims*	*Family Size*
VET-UNI	**Complements**	**Complements**	**Complements**	**Complements**	**Complements**	**Complements**
PET-UNI	No Relation	**Substitutes**	**Substitutes**	**Complements**	**Substitutes**	No Relation

Table A4: *Sensitivity Analysis: OLS Regressions of the Matched Sample (Patents Filed Since 2000)*

OLS Regression	**Forward Citations**	**Priority Claims**	**Patent Family Size**
All absent (0,0,0,0)	0.2707063***	0.6729133***	2.447906***
UNI only (1,0,0,0)	0.3737092***	0.6854601***	2.588817***
VET only (0,1,0,0)	0.2696731***	0.6176273***	2.556819***
UAS only (0,0,1,0)	0.2982506***	0.6567592***	2.513983***
PET only (0,0,0,1)	0.2854216***	0.6835451***	2.365874***
UNI & VET (1,1,0,0)	0.4393444***	0.7981931***	2.987434***
UNI & UAS (1,0,1,0)	0.3007678***	0.6672323***	2.536636***
UNI & PET (1,0,0,1)	0.2596416**	0.5894081***	2.36042***
VET & UAS (0,1,1,0)	0.2903866*	0.6620008***	2.573284***
VET & PET (0,1,0,1)	-0.010683	0.5163211***	2.253968***
UAS & PET (0,0,1,1)	0.1346262	0.6346174***	2.328577***
UNI & VET & UAS (1,1,1,0)	1.305699***	0.9198122***	2.971105***
UNI & VET & PET (1,1,0,1)	0.281363	0.6151895**	1.966687***
UNI & UAS & PET (1,0,1,1)	0.5107188***	0.6388742***	2.264072***
VET & UAS & PET (0,1,1,1)	0.7163008***	0.7836387***	2.763502***
UNI & VET & UAS & PET (1,1,1,1)	-0.4876006***	-0.0685315	1.301604***
Technology Area Dummies	YES	YES	YES
Team Size Dummies	YES	YES	YES
Priority Year Dummies	YES	YES	YES
R-squared	0.4486	0.7727	0.9374
N	31,321	31,321	31,321

Note: The dependent variables are the IHS transformed number of forward citations, number of priority claims, and patent family size.
*Significance levels: $p < 0.1$ = *, $p < 0.05$ = **, $p < 0.01$ = ****
Standard errors are clustered at the inventor team level

Table A5: *Sensitivity Analysis: Supermodularity Results with Reduced Sample (Patents Filed Since 2000)*

	H1			**H2**		
	UAS not present			UAS present		
	Forward Citations	*Priority Claims*	*Family Size*	*Forward Citations*	*Priority Claims*	*Family Size*
VET-UNI	No Relation	**Complements**	**Complements**	**Complements**	**Complements**	No Relation
PET-UNI	No Relation	**Substitutes**	No Relation	**Complements**	No Relation	No Relation