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# Does initial vocational training foster innovativeness at the company level? Evidence from German establishment data

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**Abstract:**

While an increasing number of conceptual studies postulate that vocational education and training (VET) activities have a positive impact on the innovative capacity of training companies, empirical evidence on the subject remains scarce. This study exploits establishment data from a representative survey of German companies to estimate the effects of firms' participation in initial VET on their innovation outcomes. The results based on linear probability models and instrumental variable regressions with entropy balancing show that the impact of VET activity on innovation is more ambiguous than postulated. Overall, the participation in initial VET has virtually no effect on product innovation and radical novelties. For the total population of all German companies, the positive impact of VET activities is only observable in case of process innovation. However, our results point to significant causal effects on the innovative capacities of small and medium-sized enterprises (SMEs). We conclude that companies' participation in the VET system facilitates organizational learning in training companies and knowledge transfer from VET institutions to those enterprises, which are otherwise more likely to be detached from modern technology networks. The paper concludes with implications for policy and research.

JEL: I20, J24, O31

Keywords: education; apprenticeship training; modes of innovation; innovation without R&D; SMEs

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## 1. Introduction

Over decades, scholars of innovation highlighted formal research and development (R&D) activities of firms as the critical source of innovation and the engine of technological change (Hall et al., 2010; Rammer et al., 2009; Shefer and Frenkel, 2005; Smith, 2005). They conceptualized innovation as a production process based on codified scientific and technical knowledge developed either at scientific institutes or by a company's R&D department (Aghion and Howitt, 2006; Locke and Wellhausen, 2014). In this tradition, vocational education and training (VET) below the academic level was not expected to provide any significant impetus for firm-level innovation. By contrast, recent approaches conceptualize the innovativeness of companies as an interactive learning process that is strongly based on informal exchanges within and outside of the firm (Asheim and Parrilli, 2012a; Fitjar and Rodríguez-Pose, 2013; Parrilli and Alcalde Heras, 2016). These approaches emphasize the importance of incremental and process innovation linked to manufacturing activities (Hervas-Oliver et al., 2014; Trippl, 2011; Trott and Simms, 2017) and accentuate the role of vocationally trained workers (as opposed to scientific personnel) in this process (Albizu et al., 2017; Brunet Icart and Rodríguez-Soler, 2017; Thomä, 2017). These insights have recently prompted the emergence of a number of studies arguing that the participation of businesses in the VET system fosters their innovativeness (Lund and Karlsen, 2019; Porto Gómez et al., 2018; Rodríguez-Soler and Brunet Icart, 2018; Rupietta et al., 2021; Rupietta and Backes-Gellner, 2019).

While these contributions provide well-founded conceptual arguments for the importance of VET for innovation, the empirical evidence remains sparse. The studies to date either remain conceptual (Deissinger, 2012; Harris and Deissinger, 2003; Toner, 2010) or rely upon a qualitative research design (Alhusen and Bennat, 2020; Barabasch and Keller, 2019; Lund and Karlsen, 2019; Porto Gómez et al., 2018). While qualitative studies are effective tools for descriptive purposes and inductive reasoning, they are unable to test the relevant hypotheses and substantiate the claim of a causal link. Nonetheless, empirical testing of the relationship between initial VET and innovation remains missing in the literature. In this context, the study of Rupietta and Backes-Gellner (2019) has a pioneering character. Using company-level data for 2,870 firms from Switzerland (with larger companies being overrepresented in the sample), Rupietta and Backes-Gellner (2019) show that firms participating in apprenticeship training have higher innovation outcomes. The authors establish that the effect follows an inverted u-shape along the firm size, i.e. the effects are stronger for smaller enterprises. They also report stronger effects for product rather than process innovations.

Our study aims to shed further light on the link between initial VET and innovation. We review and synthesize arguments in favor of the positive impact of VET on firm-level innovativeness, derive a number of hypotheses and test them using a representative sample of German companies. Here, we draw on an extensive survey of the Research Institute of the German Federal Employment Agency (the IAB EP dataset), which provides comprehensive information on companies' innovation activities and vocational training. We start the analysis by replicating the Swiss study of Rupietta and Backes-Gellner (2019) to directly address the question whether the results obtained by the authors should be treated as country-specific only. Since we observe treatment effects of the same magnitude as reported by the Swiss study, we conclude that the study of subject deserves further attention. In the next step, we extend the set of controls and examine the sensibility of the estimated coefficients to the inclusion of additional indicators. Most importantly, we include indicators on in-house R&D as well as continuing training, which were missing in the original study and hence may induce omitted variable bias. As expected, we observe a sharp reduction in the measures of associations. In the third step, we perform estimations based on balanced data and instrumental variable regressions to address the problems of the potential self-selection into training and endogeneity and improve the precision of the estimates. Overall, the results indicate that the impact of VET activity on innovation is more ambiguous than postulated. For the total population of all German companies, we observe no effect of VET on radical innovation and a positive effect of VET for process innovation only. Since VET is assumed to hold particular relevance for small and medium-sized enterprises (SMEs) (Alhusen and Bennat, 2020; Porto Gómez et al., 2018; Rupietta and Backes-Gellner, 2019; Thomä, 2017), we finally focus on the effects of vocational training on innovation for the subpopulation of SMEs. Results based on IV-regressions with entropy balancing lead to the conclusion that the effects of initial VET on firm-level innovation are in fact strongest in the group of smaller firms.

Overall, our study corroborates the conclusions of previous research on the positive link between VET and innovation. However, we show that the effects are weaker than postulated for the entire population of business establishments and most evident for the group of smaller enterprises, which may have few or no science-based learning routines. We conclude that organizational learning routines that evolve from participation in the VET system increase the innovative capacity of SMEs. The question whether vocational training fosters the innovativeness of individual companies has important policy implications. At present, innovation policy still tends to neglect non-R&D related sources of innovation (Hall and Jaffe, 2018; Lay and Som, 2015). As a result, policy support measures are still strongly oriented towards the science-push model of innovation, with its emphasis on promoting in-house R&D (Hirsch-Kreinsen, 2008; Som and Kirner, 2015; Thomä and Zimmermann, 2020). As such, they tend to overlook the body of empirical evidence showing that large shares of innovating companies do not report any formal R&D (Arundel et al., 2008; Hervas-Oliver et al., 2011), and still do not differ in productivity levels (Kirner et al., 2009; Som, 2012) or growth rates from R&D active companies (Rammer et al., 2009; Thomä and Zimmermann, 2020). Thus, with their traditional focus on R&D-intensive firms and high-tech start-ups, innovation policies may disregard the growth potential of large parts of the SME sector. Furthermore, overlooking the group of non-R&D innovators, they are unable to identify and promote those institutions that facilitate and support less-R&D-oriented modes of innovation at the company level. Our study shows that VET institutions help to foster the innovativeness of less R&D-intensive SMEs and innovation policy may be well advised to promote and assist a further purposive development of these education institutions.

The remainder of the paper is structured as follows. In the following section, we review and synthesize arguments from the conceptual and empirical studies analyzing how initial VET contributes to knowledge transfer, learning and innovation (Section 2). Here, we derive our central hypotheses on the association between vocational training and different patterns of firm-level innovation. In the next sections, we introduce the dataset (Section 3), discuss the estimation strategy (Section 4) and present the main results both from baseline specifications (Section 5.1) and extended models (Sections 5.2-5.3). The paper concludes with implications for policy and further research.

## 2. The link between vocational education and innovation

### *2.1. VET and the DUI mode of innovation*

Traditionally, researchers have conceptualized innovation as the production and use of codified scientific and technical knowledge, as a process based on scientific principles and formal R&D practices (Jensen et al., 2007). Knowledge production has been assumed to take place in scientific institutions or formal R&D departments of industrial leaders and build on prior knowledge and skills of scientific personnel (Aghion, 2008; Aghion and Howitt, 2006). In this context, the human capital of academically-trained personnel (e.g. employees with a PhD or master in natural sciences or engineering) has been seen as the main precondition for a company’s ability to absorb valuable knowledge inputs from outside the firm (Cohen and Levinthal, 1990, 1989). Unsurprisingly, this research tradition did not assume that VET-based qualifications below academic levels holds much relevance for technological progress and innovation.

The more recent literature takes a rather holistic approach to innovation, emphasizing the role of experience-based, locally-embedded tacit knowledge (Grillitsch and Rekers, 2016; Thompson, 2010) and interactive learning within and external to the firm (Fagerberg et al., 2012; Lundvall, 1985; Pittaway et al., 2004) for innovation. This approach closely relates to Jensen et al.'s (2007) conceptual differentiation between two distinctive modes of innovation. The first one – labeled the STI mode – resembles the traditional understanding of the innovation process. It is based on science, technology and innovation (STI) and characterized by the production and use of explicit, codified and scientific knowledge. The second mode is based on doing, using and interacting (DUI) and relies upon the interactive use of experience-based know-how, which is often highly localized and of an implicit nature. The DUI approach builds on the concepts of learning-by-doing (Arrow, 1962), learning-by-using (Rosenberg, 1982) and learning-by-interacting (Lundvall and Johnson, 1994), which imply that not only formalized R&D activities but also practical experience in production and customer relations result in competence building and knowledge inflow, which in turn facilitates innovation outcomes. Within the DUI mode, practical problem-solving skills developed in production-related environments hold paramount importance for innovation. Moreover, organizational learning and creating a corresponding business culture are the micro foundation of DUI mode learning in innovating firms (Asheim and Parrilli, 2012b). As a result, some studies in the literature on DUI mode innovation stress the importance of vocational qualifications as an important input into the business innovation process (Thomä, 2017; Thomä and Zimmermann, 2020).

STI and DUI modes of innovation are often associated with different innovation outcomes. The science-driven STI mode is expected to produce more radical, market-shaping, disruptive innovation. By contrast, incremental innovations that involve only minor modifications and improvements of existing technologies, products and services are primarily associated with DUI processes (Nunes and Lopes, 2015). Incremental product modifications are assumed to be mainly customer-driven, and they result from the adaptation and improvement of existing products and services to specific needs of individual consumers (Kirner and Som, 2015). Incremental process innovations in terms of continuous improvements, optimization and the cost efficiency of business processes arise as a result of cumulative learning among employees (Dutton and Thomas, 1984; Matthews et al., 2017). According to Toner (2010), VET trained workers play a critical role in such incremental innovation activities. Similarly, Thomä (2017) and Thomä and Zimmermann (2020) argue that DUI mode learning, the introduction of incremental innovation and the relevance of VET-based qualifications are closely intertwined.

According to Jensen et al. (2007: 684), DUI-based workplace learning may occur as an "unintended by-product", but it can also be intentionally fostered by building organizational structures, which enhance knowledge exchange and informal learning. While previous literature on organizational learning focused on the role of flexible organizational practices like task groups (Argote and Miron-Spektor, 2011), quality circles or task rotation (Wood, 1999), recent literature starts to devote attention to more established and continuous forms of organizational learning, like the initial or continuing training of skilled workers (Barba Aragón et al., 2014; Bauernschuster et al., 2009; Jaw and Liu, 2003). Thus, training activities are increasingly acknowledged as an essential element of DUI mode learning and innovation (Alhusen and Bennat, 2020; Apanasovich, 2016).

*2.2. The role of VET in organizational learning*

In Germany, initial VET is often associated with a distinct learning and training culture (Deissinger, 2015, 2012; Harris and Deissinger, 2003; Pilz, 2009; Wiemann and Pilz, 2020). However, only a few recent studies explicitly conceptualize the VET system as an institutional mechanism for organizational learning and knowledge spillover and a driver of SMEs' absorptive capacities (Barabasch and Keller, 2019; Proeger, 2020; Rupietta et al., 2021). Generally, the concept of organizational learning refers to the transformation of individual knowledge into organizational knowledge and the establishment of organizational routines that sustainably promote knowledge creation and dissemination (Argyris and Schon, 1978; Popper and Lipshitz, 2000). Organizational learning as a multilevel process occurs when the knowledge and skills of individual workers and groups become embedded in the organization's practices (Crossan et al., 2011) and thus improve business performance and innovativeness (Jiménez-Jiménez and Sanz-Valle, 2011; Santos-Vijande et al., 2012). Gaining experience is crucial for growing knowledge stocks (Argote and Miron-Spektor, 2011; Fiol and Lyles, 1985).

In accordance with this concept, Barabasch and Keller (2019) argue that companies participating in the VET system not only support and encourage independent learning of their apprentices, but they also introduce "innovative structural practices" that shape the learning culture of the whole enterprise. Similarly, Harris and Deissinger (2003) note that apprenticeship training involves not only the "picking up of skills", but also assimilating the tacit knowledge of the trade, along with its cultural values, ways of interacting and manufacturing standards by means of "learning-by-immersion". Alhusen and Bennat (2020) argue that participation in the VET system helps to develop a new organizational culture that promotes "learning-by-training". According to Thomä (2017), the strength of the VET system is associated with the interactive character of dual training, enabling VET graduates to solve complex problems and interact with engineers and scientists in innovation projects.

All of these studies suggest that the innovative impact of the VET system stems from both internal knowledge creation and external knowledge transfer (Nonaka, 1994), namely from the combination of endogenous and exogenous learning. Endogenous learning occurs within the firm and is associated with localized skill enhancement (Dutton and Thomas, 1984). While conducting initial VET, tacit knowledge is transferred from experienced practitioners to apprentices. The internal knowledge transfer is seen as a comprehensive process that is not reduced to "teaching skills" but rather conceptualized as a complex process of trade-based socialization (Harris and Deissinger, 2003) and complemented by experience-based practical expertise (Thomä, 2017). Exogenous learning is associated with the acquisition and absorption of new information from external resources (Dutton and Thomas, 1984), like VET colleges (Wieland, 2015). In this view, apprentices act as "hybrid agents", integrate external knowledge and moderate organizational change (Rupietta et al., 2021). The VET system helps companies to institutionalize such internal and external forms of learning (Deissinger, 2015; Wieland, 2015) and ensures a constant flow of knowledge within the organization (i.e. between employees) and across organizational boundaries from the institutions of the VET system to individual business establishments (Rupietta et al., 2021; Rupietta and Backes-Gellner, 2019).

*2.3. Empirical evidence*

To our knowledge, Toner (2010) was the first researcher to discuss the role of vocational training in innovation in more detail. His study focuses on the patterns of innovation activity in Australia, which he describes as being concentrated on a range of low and medium technology sectors and non-R&D-intensive firms that heavily rely on technology sourcing rather than own research activities (i.e. a pattern of DUI type). The author argues that the effectiveness and efficiency of innovation activities in this less R&D intensive knowledge environment critically depend on the capacity of the production workforce to engage creatively in problem-solving. The VET system is seen as crucial for this process. According to Toner (2010), it plays a critical role in skills creation, knowledge diffusion and the development of the workforce's absorptive capacity. He also stresses the importance of vocational education institutions, which are highly responsive to the particular needs of local industries, offer customized training programmes, serve as intermediaries between equipment producers and local businesses and present new technologies to their customers. Building on the arguments of Rosenfeld (1998), this study recapitulates that all of these functions are especially vital for SMEs, which often lack the resources and competences to scout the newest knowledge and technologies. Taken together, Toner (2010) conceptualizes the VET system as an institutional learning environment that promotes localized skill enhancement and technology diffusion through initial VET.

The role of vocational education institutions for the functioning of regional innovation systems is further examined in the Spanish study of Porto Gómez et al. (2018) and the Norwegian study of Lund and Karlsen (2019). Porto Gómez et al. (2018) use a survey design to analyze the role of VET training centers as agents of knowledge exchange and dissemination in the Basque country. They conclude that for many local firms, VET centers represent the main source of knowledge and hence play a "pivotal role" in the innovation processes of these companies. Lund and Karlsen (2019) conduct nineteen in-depth, semi-structured interviews in two Norwegian manufacturing regions and re-establish the result of the Spanish study, concluding that vocational colleges are important sources of knowledge for local firms. Similar to Toner (2010), they report the high responsiveness of vocational institutions to the needs of the local business sector, show how industrial actors and vocational schools cooperate in developing educational programs and demonstrate how the manufacturing industry and vocational education institutions co-evolve with new technological developments. Thus, both studies stress that the participation in initial VET contributes to establishing continuous knowledge flows between VET institutions and local business establishments.

The recent Swiss study of Rupietta and Backes-Gellner (2019) goes a step beyond these considerations and analyzes in detail how participation in the VET system promotes technology diffusion and innovation. They describe the Swiss dual system of apprenticeship training and highlight the role of institutionalized curriculum development and updating processes as a central channel of knowledge diffusion, and hence as major driver of DUI mode learning in training companies. In Switzerland (as in Germany), vocational training is based on nationally-binding, occupation-specific training curricula, which ensure a high level and transferability of vocational skills (Mueller and Schweri, 2015; Wolter and Ryan, 2011). These curricula are regularly updated to not only cover widespread knowledge and well-established technologies, but also to provide information about specialized technologies or new technological developments that are not generally used in the day-to-day operations of an individual company. In essence, in the model of Rupietta and Backes-Gellner (2019) the involvement of the leading-edge companies in this institutionalized curricula-updating process fosters the distribution of new knowledge and technologies across the broad range of training companies and therefore enhances their innovation capacities. According to the authors, companies participating in initial VET are confronted with new technologies of the industry leaders, learn about them and – because of this – have competitive advantages over firms that do not participate in apprenticeship training. While large companies are primarily those that provide the innovative input into the curricula-updating process, SMEs are expected to profit most from this knowledge diffusion and the subsequent adaptation of new knowledge inputs to their individual needs. Consequently, Rupietta and Backes-Gellner (2019) expect the innovation effects of participation in the VET system to be stronger for smaller companies.

### *2.4. Hypotheses and research design*

Taken together, the existing studies argue that participation in the VET system enables individual companies to enhance their technical competences, raise their absorptive capacity and – even more importantly – establish structures and relationships that strengthen the continuous inflow of new knowledge into business establishments and foster a learning climate. The innovativeness of training companies should therefore be higher than for non-participants. Previous research further stresses the importance of VET institutions – teaching centers as well as training curricula and their continuous updating – as a main channel of technology transfer from technological leaders and technology enablers to technology followers. In this context, participation in the VET system should have the strongest impact on innovation in SMEs, which are not at the technological frontier of their industry and often lack necessary resources and competencies for technology sourcing. The available studies also highlight that skill enhancement associated with vocational training tends to result in incremental innovation rather than radical, market-shaping outcomes. Finally, the empirical results of Rupietta and Backes-Gellner (2019) suggest that initial VET activities have a stronger impact on product innovation activities than process innovation. Building on these arguments, we derive the following hypotheses on the role of initial VET in firm-level innovation, which we will test in the following sections of the paper:

H1: Companies participating in the VET system have higher innovation outcomes than non-participants.
H2: Participation in initial VET fosters the introduction of incremental rather than radical innovation.
H3: Participation in initial VET has a stronger effect on product rather than process innovations.
H4: The impact of initial VET on innovation is strongest for SMEs.

## 3. Data

To investigate the link between vocational training and innovation, we use cross-sectional data from an extensive panel survey of the German Federal Employment Agency: the IAB EP dataset. The IAB EP is an employer survey that is representative of all industries and company size classes in Germany. The sampling frame in the IAB EP survey is the Establishment File of the Federal Employment Agency, which contains all business units with at least one employee covered by social security. Thus, one-person establishments or establishments with marginal employees (i.e. employees who are not subject to social security provisions) are not included in the target sample. This limitation does not affect our study because VET trainees are treated as regular employees in German social security schemes. Companies providing initial VET are therefore fully covered by the sampling scheme. Ellguth, Kohaut and Möller (2014) provide further details on the sampling of the IAB EP dataset and the overall design of the survey.

We analyze data for 2017, which we access via a remote data execution system (JoSuA) of the Research Data Centre (FDZ) of the German Federal Employment Agency. To ensure the representativeness of the results to the population of all German establishments, we use cross-sectional weights provided in the dataset (for more details on this, see Fischer et al., 2008). Thus, in contrast to Rupietta and Backes-Gellner (2019) – who report an oversampling of large enterprises in the Swiss dataset – we can rely on fully representative data in our study. The dataset includes information on 15,421 establishments, 36.3% of which report innovation outcomes and 28.6% report VET activities. A full description of all variables and the respective descriptive statistics by VET status is given in Table 1.

Our main variables of interest are indicators for innovation outcomes and initial VET. The IAB survey asks respondents a number of questions on innovation activities that we can use to construct our dependent variables. Following Rupietta and Backes-Gellner (2019), we distinguish between general, product and process innovation. Additionally, we differentiate between radical and incremental product innovation to test hypothesis 2. The underlying survey questions fully comply with the Oslo Manual guidelines on measuring firm-level innovation (OECD and Eurostat, 2018)[1]. Contrary to Rupietta and Backes-Gellner (2019), we do not have any information on the companies' patenting strategy, so we cannot use an indicator for patent applications in our research setting.

The survey further gathers extensive information concerning VET activities of individual companies. We construct our primary variable of interest – the binary training indicator "training company" – based on information in the IAB survey on whether a company employs VET trainees (i.e. apprentices) or not. In addition, we also use the comprehensive information on the qualification structure of the company's workforce provided in the dataset. Here, we construct a metric variable describing the share of VET trainees among all employees, along with further metric variables describing the share of workers with different qualification levels.

We divide the sample by VET status and report descriptive statistics for training companies and non-trainers in Table 1. We observe that training companies outperform other firms in a number of dimensions. First of all, training companies more often report innovation outcomes than non-training ones. Thus, based on descriptive statistics, we would expect the training status to have a noticeable impact on firm-level innovativeness. However, training companies are also larger on average, face fiercer competition and have stronger propensities to invest in equipment, provide continuing training and conduct R&D themselves (Table 1). Hence, the distribution of the covariates is strongly unbalanced and we should consider this in our estimation strategy. To address this issue, we use a large number of control variables in our estimation models. Most importantly – and in contrast to Rupietta and Backes-Gellner (2019) – we include indicators for R&D, continuing training and investment in the extended control strategy. Additionally, to improve the precision of the estimates of the association between VET and innovation, we perform estimations based on balanced data. Finally, we also perform instrumental variable regressions to retrieve causal estimates. We explain the motivation for the usage of the different estimation strategies and the associated problems in more detail in the following section.

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[1] The questions asked in the IAB survey 2017 were: "In the last business year of 2016, did your establishment improve or further develop a product or service which had previously been part of your portfolio?" (*product innovation*); "In the last business year of 2016, did your establishment start to offer a product/service that had been available on the market before?" (*new-to-the-firm product innovation*); "Have you started to offer a completely new product or service in the last business year of 2016 for which a new market had to be created?" (*radical product innovation*); "Did you develop or implement procedures in the last business year of 2016 which have noticeably improved production processes or services?" (*process innovation*).

Table 1. Descriptive statistics

| | | All companies | | Training companies | | Non-training companies | |
|---|---|---|---|---|---|---|---|
| | **Description** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** |
| ***Dependent variables*** | | | | | | | |
| General innovation | 1 if firm conducted product and/or process innovation | 0.36 | 0.48 | 0.44 | 0.50 | 0.33 | 0.47 |
| Product innovation | 1 if firm conducted product inno. | 0.35 | 0.48 | 0.42 | 0.49 | 0.32 | 0.47 |
| Process innovation | 1 if firm conducted process inno. | 0.10 | 0.30 | 0.14 | 0.35 | 0.09 | 0.28 |
| Radical innovation | 1 if firm conducted new-to-market product innovations | 0.05 | 0.23 | 0.07 | 0.25 | 0.05 | 0.22 |
| Incremental innovation | 1 if firm conducted product innovation which is not new to the market | 0.34 | 0.48 | 0.42 | 0.49 | 0.32 | 0.46 |
| ***Explanatory variable*** | | | | | | | |
| Training company | 1 if firm employs VET trainees | 0.29 | 0.45 | 1.00 | 0.00 | 0.00 | 0.00 |
| ***Control variables (step 1: replication)*** | | | | | | | |
| Company size | Total number of employees | 18.82 | 122.22 | 42.06 | 222.49 | 9.52 | 28.30 |
| Share of workers without education | Employees with no specific vocational education in total employment (%) | 0.18 | 0.26 | 0.15 | 0.20 | 0.20 | 0.28 |
| Share of VET trainees | VET trainees in total employment (%) | 0.03 | 0.07 | 0.10 | 0.11 | 0.00 | 0.00 |
| Share of workers with vocational qualification | Employees with completed vocational training in total employment (%) | 0.49 | 0.29 | 0.58 | 0.25 | 0.45 | 0.30 |
| Share of workers with university degree | Employees with higher education in total employment (%) | 0.06 | 0.16 | 0.05 | 0.14 | 0.07 | 0.17 |
| Competitive pressure | 1 for medium / substantial competitive pressure | 0.68 | 0.47 | 0.72 | 0.45 | 0.66 | 0.47 |
| Demand expectation | 1 if company expects increasing business volume next year | 0.26 | 0.44 | 0.30 | 0.46 | 0.25 | 0.43 |
| Foreign company | 1 if company is foreign owned | 0.04 | 0.21 | 0.03 | 0.18 | 0.05 | 0.22 |
| Shortage of skilled workers | 1 if a company reports lack of skilled workers | 0.17 | 0.37 | 0.26 | 0.44 | 0.13 | 0.34 |
| ***Extended set of controls (step 2: further controls)*** | | | | | | | |
| Continuing training | 1 if a company provides continuing training to their employees | 0.53 | 0.50 | 0.76 | 0.43 | 0.44 | 0.50 |
| R&D activities | 1 if a company conducts in-house R&D | 0.06 | 0.23 | 0.08 | 0.27 | 0.05 | 0.21 |
| Investment activities | 1 if a company made investments in 2016 | 0.52 | 0.50 | 0.64 | 0.48 | 0.47 | 0.50 |
| Technical equipment | State of a company's technical equipment (1 "state-of-the-art" – 4 "out of date") | 2.77 | 0.78 | 2.85 | 0.76 | 2.74 | 0.78 |
| Export activities | 1 for exporting companies | 0.12 | 0.33 | 0.14 | 0.35 | 0.11 | 0.32 |
| Broadband connection | 1 if a company has high-speed internet access | 0.74 | 0.44 | 0.79 | 0.41 | 0.72 | 0.45 |
| Family business | 1 if a company is family-controlled | 0.89 | 0.31 | 0.85 | 0.36 | 0.91 | 0.29 |
| ***Instrument*** | | | | | | | |
| VET training license | 1 if firm has a permission to conduct initial VET via trainer aptitude examination | 0.53 | 0.50 | 1.00 | 0.00 | 0.34 | 0.48 |

Source: IAB Establishment Panel, Wave 2017, weighted data. Data access was provided via remote data execution (Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB), 2017). DOI: 10.5164/IAB.IABBP9317.de.en.v1.

**4. Estimation strategy**

We start our analysis by estimating models with different specifications and sets of controls using standard ordinary least square estimators. Our dependent variable is an indicator, so we refer to the estimations as linear probability models (LPMs) (Angrist & Pischke 2009). In analogy to the Swiss study of Rupietta and Backes-Gellner (2019), we rely on LPMs rather than probit or logit models for consistency and computational reasons (the subsequent IV estimations with weighting option are only available with a linear model). Generally, the choice of the estimation model will hardly affect the results, given that LPMs and non-linear models based on link functions are known to deliver similar results (Angrist and Pischke, 2009).

Our basic estimation model is thus given by:

$$INNO_j = \gamma_0 + \gamma_1 VET_j + \sum_{k=1}^{K} \gamma_k x_{kj} + e_j$$

where INNO denotes the innovation indicator (equal 1 for innovating companies, and 0 otherwise), VET takes the value of 1 if the firm is currently engaged in initial VET activities, k denotes the number of control variables, j denotes the number of companies and e is the error term.

We begin our analysis with the replication of the models estimated by Rupietta and Backes-Gellner (2019). Their set of controls include firm size, the educational composition of a firm's workforce, competition measures, an indicator for a shortage of skilled workers and indicators for foreign-owned firms, economic sector, year and region. Based on our dataset, we are able to construct a comparable set of controls with some minor differences in the scaling of some variables (see Table 1). First, our workforce qualification variable includes four categories rather than five. Second, our competition measures do not refer to price and non-price competition, but rather a question asking survey respondents to assess the pressure of competition in their market (1 for medium or substantial pressure). Third, as an alternative to the control variable on demand changes in the Swiss study, we use information on the business volume expectation (1 if a company expects increasing business volume in the next year). Like Rupietta and Backes-Gellner (2019), we are also able to control for economic sector, firm size, a shortage of skilled workers, foreign ownership and regional dummies.

In the second step of our analysis, we extend the set of controls in the estimated models. Most importantly, Rupietta and Backes-Gellner (2019) are unable to control for in-house R&D in their study. This is an important limitation, because formal and institutionalized R&D activities are known to be a major input to the innovation process at the company level, especially in companies following the STI mode of innovation (Jensen et al. 2007; Hall and Jaffe, 2018). Due to the wide scope of the IAB EP survey, we are able to include the R&D indicator and additionally an indicator for continuing training. We assume that both R&D and continuing training activities increase the knowledge stock of companies and affect their knowledge flows, both of which should have a positive impact on firm-level innovativeness, in particular regarding product innovation (Bauernschuster et al., 2009; Fagerberg et al., 2010).

Further, we consider indicators on investment and the technical state of equipment as further important inputs into the knowledge production process. The technical state of equipment reflects a firm's technological endowment and its ability to convert resources into innovative outputs. Investments in new production facilities, plants or equipment increase this stock and capabilities (Barney, 1991; Heidenreich, 2009). The literature shows that investment activities may be inversely related to R&D: firms may substitute their own technology development with technology sourcing (Santamaría et al., 2009). We can include both indicators as control variables by drawing on the questions in the IAB EP survey concerning the technical state of a company's equipment (1 "state of the art" – 4 "out of date") and its investment activities (1 for investments in 2016, 0 otherwise).

Drawing upon additional evidence in Akerman et al. (2015) and their discussion of the link between productivity and digital transformation, we further control for high-speed internet access. Finally, we also include general company-specific controls, such as dummies for family-owned businesses (Zahra, 2012) and export activities, as these indicators have both been shown to affect firm-level innovativeness (Peters and Rammer, 2013).

The main challenge in estimating the impact of initial VET on firm-level innovativeness is that a firm's participation in the dual VET system may not be random. Thus, when deciding on the estimation approach, it is necessary to address the problem of a potential self-selection into training. Assuming selection on observables, we could cope with the potential selection bias by applying either matching (Abadie and Imbens, 2011; Zhao, 2004) or entropy balancing (Hainmueller, 2012). Both techniques are data pre-processing methods that aim to eliminate the self-selection bias by balancing out the set of observable characteristics. Entropy balancing (EB) is a technique that has recently emerged in the literature on treatment effects. It is to be understood as a generalization of the propensity score weighting approach (Hainmueller, 2012). We have opted for EB in our study for three reasons: first, EB allows us to include a larger set of balance constraints compared to matching; second, in relying on EB we can retain the full information from the original data and do not have to discard observations (as would be the case with matching); and third, the method is also computationally attractive, as the search algorithm attains the weighting solution within seconds, even with a large data set like ours. By contrast, matching procedures often involve an intricate search process, which often does not result in a satisfying level of covariate balance and – in some cases – can even prevent the reduction of potential self-selection bias (Hainmueller, 2012; Hainmueller and Xu, 2013; Zhao and Percival, 2017).

Thus, EB allows us to cope with problems associated with self-selection based on observables. However, the estimated coefficients may also be biased by unobserved characteristics (omitted variables), endogeneity due to reverse causality or the simultaneity of companies' decisions (Wooldridge, 2013). For example, one could argue that innovation activities trigger a higher demand for skilled workers, which may affect the decision to start training activities within the dual VET system (Jansen et al., 2015; Rupietta and Backes-Gellner, 2019). This would imply problems associated with reverse causality. Similarly, one could argue that we should control for managerial ability (which unfortunately is unobservable in our dataset), as the human capital of managers or owners has been shown to have a positive impact on firm-level innovativeness (Andries and Czarnitzki, 2014; Kraiczy et al., 2015; McGuirk et al., 2015; Moilanen et al., 2014).

The method of choice to cope with omitted variables bias or endogeneity issues in a cross-sectional design is the instrumental variables (IV) approach (Acemoglu et al., 2001; Acemoglu and Angrist, 2000; Angrist and Pischke, 2009; Wooldridge, 2013). The main idea of the IV approach is to use a variable that is correlated with the explanatory variable (i.e. a company's decision to train in our case) but does not have a direct impact on the innovation output of a firm. Rupietta and Backes-Gellner (2019) use two instruments in their study. The first one is based on the different training traditions in the Swiss regions: firms located in German-speaking regions are typically more likely to offer initial VET than companies located in French- or Italian-speaking regions of Switzerland. Their second instrument is based on company age, whereby the authors argue that a firm's age reflects a longer or shorter training experience and that establishments with a longer training tradition more heavily rely on initial VET. Assuming that older and German-speaking companies do not show a higher level of innovativeness independent of their training decisions, the study relies on these instruments for identification.

As we use German data in our study, we cannot construct an instrument based on regional variation. We could rely on the sharp East-West distinction, although it this case we would disregard the overall lower level of innovativeness of Eastern German companies (Peters and Rammer, 2013), which is mainly driven by structural causes. We also refrain from instrumenting on company age as there is evidence that on average older firms are less engaged in innovation activities than younger ones, namely company age should in fact have a direct impact on firm-level innovativeness (Baumann and Kritikos, 2016). Instead, we use information on official training permission (1 if a firm has a permission to conduct initial VET via a training license, 0 otherwise) as an instrument for training activity. This instrument clearly correlates with training activities, as the official permission is a mandatory requirement to provide training. However, not all companies that are formally allowed to train VET trainees actually engage in initial VET. In fact, approximately only half of the companies holding a VET training license also train apprentices (Federal Institute for Vocational Education and Training (BIBB), 2020).

Applying the training permission as an instrument, we have to assume that the impact of initial VET on firm-level innovativeness stems from a continuous engagement in knowledge flows and organizational learning arising within the institutional framework of the German VET system rather than from the permission itself. The main objection here could be that to receive a training permission a company has to provide an appropriate training environment, which may include investing in technical equipment and employing competent instructors (Federal Institute for Vocational Education and Training (BIBB), 2018). Both of these aspects may directly affect the innovativeness of the respective training companies. Hence, to address these potential concerns, we control for the technical state of companies' technical equipment and the qualification structure of their workforce in our estimation models. On this basis, we assume the conditional independence of a company's VET training license and its innovation outcomes.

## 5. Results

### *5.1. Baseline results*

We start with the presentation of a basic replication of the Swiss study of Rupietta and Backes-Gellner (2019). According to the results displayed in Table 2, German companies participating in initial VET have a 7.8% higher probability of being innovative than non-training companies. Thus, the point estimate in our estimation sample is one percentage point higher than in the Swiss study, which reports a point estimate of 6.8%. Turning to product innovation, we observe a marginal effect of 0.076, which is again slightly higher than the coefficient reported in the Swiss study (0.061). We further observe a positive association between initial VET activities and process innovation (0.050). Here, our results differ from Rupietta and Backes-Gellner (2019), who report a non-significant marginal effect of 0.034. Overall, the replication results provide evidence in favor of the hypothesis concerning the overall positive association between initial VET and general firm-level innovativeness (H1). The effect sizes and significance levels in the German sample are slightly higher compared to those reported in the Swiss study. Moreover, we find some support for the hypothesis of a stronger effect of initial VET on product than process innovation (H3).

Table 2. Baseline results

| | **Linear probability models** | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| ***For comparison: Rupietta and Backes-Gellner (2019) results based on Swiss data*** | | | | | |
| Training company | 0.068*** | 0.061*** | 0.034 | not reported | not reported |
| ***Replication results based on German data*** | | | | | |
| Training company | 0.078*** | 0.076*** | 0.050*** | 0.008 | 0.075*** |
| $R^2$ | 0.103 | 0.103 | 0.064 | 0.044 | 0.101 |
| Adj. $R^2$ | 0.100 | 0.099 | 0.061 | 0.040 | 0.098 |
| Observations | 11,812 | 11,812 | 11,777 | 11,781 | 11,812 |

Notes: The table displays marginal effects from linear probability models with weighted data, estimated for different dependent variables (binary indicators for general, product, process, radical and incremental innovation). Further controls include firm size, indicators for the educational composition of a firm's workforce, competition measures, an indicator for a shortage of skilled workers, indicators for foreign ownership, economic sector and sixteen federal states. The coefficient estimates for the control variables are reported in the Appendix (Table A. 1). Significance levels are based on robust standard errors and denoted as: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Turning to the estimation models for radical and incremental innovations (Table 2, Columns 4 and 5), we observe the pattern of results that we expected based on the theoretical literature: the positive impact of initial VET on firm-level innovativeness primarily relates to incremental (DUI) learning and innovation (marginal effect of 0.075). In case of radical innovation, the respective treatment coefficient is almost zero and not significant (0.008). These results are consistent with hypothesis 2, postulating a stronger effect on incremental rather than radical innovation.

### *5.2. Results based on the extended set of controls*

In their pioneering study, Rupietta and Backes-Gellner (2019) are unable to control for two important inputs into the knowledge production process that are associated with different modes of learning: the existence of in-house R&D activities and continuing training of employees. As highlighted in Section 4, this is an important limitation, which can upward bias the results of the baseline specification due to omitted variables. Therefore, to check the robustness of the baseline results to the inclusion of additional covariates, we extend the control strategy and add a number of additional variables to the estimation models. In particular, we include indicators on R&D, company-financed continuing training and several technology and investment dummies. Additionally, we control for a firm's digital infrastructure and a number of other company-level characteristics that have been shown to affect the propensity to innovate (and are listed in Table 1). The estimation results for the full set of controls are given in Table 3.

As expected, the extended control strategy significantly reduces the estimated association between initial VET and all outcome measures of innovation. The coefficients on participation in VET remain positive for all but radical innovation, although they are much lower and partly not significant. In particular, we cannot observe any positive impact of initial VET on radical innovation, which is a result consistent with our theoretical reasoning (hypothesis 2). However, there is also no statistically significant association between initial VET and general, product or incremental innovation. We can only observe a positive association between initial VET activities of training companies and their propensity to introduce process innovations. According to the model estimates of Table 3, companies that participate in the VET system have a 3.0% higher probability of reporting improved production processes or services. Hence, based on an extended set of controls, we find no evidence in favor of hypotheses 1, 2 and 3. Instead, we observe a general link between initial VET and the introduction of process innovation. This novel finding can probably be explained by the fact that process innovations often are a result of hands-on experience of employees and their intimate familiarity with the technological processes involved. Compared to product innovation, the knowledge associated with improvements in production and services processes thus often contains a relatively high degree of tacitness (Gopalakrishnan et al., 1999), which may explain the role of initial VET in this context.

A closer look at the control variables further explains the reasons for the change in the estimated coefficients (Table 3). In line with previous research (Hall and Jaffe, 2018; Heidenreich, 2009), we observe a very strong association between R&D and all output measures of innovation. Companies that report formal R&D activities have between a 19.5% and 30.2% higher probability (depending on the type of innovation) of reporting innovation outputs. Similarly, companies that invest in new technology and report a more advanced technological equipment display a significantly higher probability to innovate, which is also a result known from the literature (Barney, 1991; Smith, 2005). Like Bauernschuster et al. (2009) and Peters and Rammer (2013), we also observe a positive impact of continuing training on innovation. Leaving out these central inputs into the knowledge production process leads to overestimating the impact of initial VET activities on the innovativeness of individual companies. Hence, these results could cast some doubt on the overall importance of participation in initial VET activities for innovation in companies.

Table 3. Results of models with the extended control strategy

| | **Linear probability models** | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| Training company | 0.015 | 0.012 | 0.030*** | -0.007 | 0.011 |
| ***Controls*** | | | | | |
| Company size | 0.000 | 0.000 | 0.000*** | 0.000 | 0.000 |
| Share of unqualified workers | -0.078* | -0.098** | 0.016 | 0.001 | -0.099** |
| Share of qualified workers | -0.005 | -0.027 | 0.032 | 0.021 | -0.028 |
| Share of university graduates | 0.029 | 0.015 | 0.037 | 0.034 | 0.009 |
| Shortage of skilled workers | 0.020 | 0.022 | 0.004 | 0.003 | 0.023 |
| Continuing training | 0.083*** | 0.082*** | 0.017 | 0.013* | 0.080*** |
| R&D activities | 0.285*** | 0.288*** | 0.302*** | 0.195*** | 0.281*** |
| Investment activities | 0.117*** | 0.113*** | 0.055*** | 0.023*** | 0.114*** |
| Technical equipment | 0.067*** | 0.067*** | 0.021*** | 0.014*** | 0.068*** |
| Export activities | 0.163*** | 0.159*** | 0.057** | 0.004 | 0.157*** |
| Competitive pressure | 0.060*** | 0.062*** | 0.017* | -0.006 | 0.065*** |
| Demand expectation | 0.080*** | 0.075*** | 0.046*** | 0.031*** | 0.075*** |
| Broadband connection | 0.030* | 0.035** | 0.003 | 0.006 | 0.035** |
| Foreign company | -0.037 | -0.036 | 0.010 | 0.002 | -0.038 |
| Family business | -0.071*** | -0.076*** | -0.011 | -0.019 | -0.077*** |
| Observations | 10,631 | 10,631 | 10,614 | 10,616 | 10,631 |
| $R^2$ | 0.176 | 0.177 | 0.133 | 0.084 | 0.175 |
| Adj. $R^2$ | 0.172 | 0.173 | 0.129 | 0.080 | 0.171 |

Notes: The table displays marginal effects from linear probability models with weighted data, estimated for different dependent variables (binary indicators for general, product, process, radical and incremental innovation). Further controls include indicators for economic sector and sixteen federal states. Significance levels are based on robust standard errors and denoted as: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

However, as noted above, the results in Table 3 may be biased due to potential self-selection into initial VET. To address this issue, we balance the estimation sample on the set of observable variables, i.e. we equate the covariate distribution across trainers and non-trainers. The results of estimations based on balanced data are reported in Table 4. In LPMs, we obtain coefficients that are slightly higher than those estimated in the weighted regressions reported in Table 3. We still do not observe any impact of the participation in initial VET on radical innovation, which is again consistent with hypothesis 2. For all other innovation measures of innovation, we now observe significant treatment effects between 3.1% and 4.0%. Thus, the results based on balanced data point to the existence of a positive association between companies' participation in initial VET and firm-level innovation for general, product, process and incremental innovation. However, the measures of associations are lower than those reported in the estimations on the basic set of controls (Table 2) and those reported in the Swiss study of Rupietta and Backes-Gellner (2019). Above that, the models indicate that the strongest effects on innovation outcomes are associated with companies' own R&D investments and the share of highly-qualified workers (the full set of controls is reported in the Appendix in Table A. 2). In comparison, the estimated effect for initial VET is much lower. Nonetheless, despite the hitherto-unaddressed potential endogeneity concerns, these results support our theoretical assumption that there is a positive link between initial VET and innovation.

Table 4. Results based on balanced data

| | Regressions based on balanced data | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| ***LPM*** | | | | | |
| Training company | 0.037*** | 0.039*** | 0.031*** | -0.000 | 0.040*** |
| $R^2$ | 0.215 | 0.211 | 0.162 | 0.094 | 0.206 |
| Adj. $R^2$ | 0.212 | 0.208 | 0.158 | 0.090 | 0.203 |
| ***IV regression, 2nd stage*** | | | | | |
| Training company | 0.035 | 0.032 | 0.043** | -0.012 | 0.037 |
| $R^2$ | 0.215 | 0.211 | 0.162 | 0.094 | 0.206 |
| Adj. $R^2$ | 0.212 | 0.208 | 0.158 | 0.089 | 0.203 |
| ***IV regression, 1st stage*** | | | | | |
| VET training license | 0.677*** | 0.677*** | 0.677*** | 0.677*** | 0.677*** |
| Cragg-Donald Wald F statistic | 4,937 | 4,937 | 4,922 | 4,924 | 4,937 |
| Kleibergen-Paap rk Wald F statistic | 6,279 | 6,279 | 6,245 | 6,247 | 6,279 |
| Observations | 10,631 | 10,631 | 10,614 | 10,616 | 10,631 |

Notes: The table reports coefficients from the linear probability model (upper panel) and instrumental variable regressions (lower panel) based on data weighted with maximum entropy weights. The results of the balancing procedure are given in the Appendix (Table A. 4). Dependent variables are indicators for innovation activity (general, product and process innovation, radical and incremental innovation). The set of controls includes all controls listed in Table 3 (firm size, indicators for the educational composition of a firm's workforce, indicators for a shortage of skilled workers, continuing training, R&D, investment and export activities, competition measures, demand expectation, broadband availability, state of technical equipment, indicators for foreign firms, family business, economic sector and sixteen federal states). The coefficient estimates for the control variables are reported in the Appendix (Table A. 3). Significance levels are denoted as: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

In a final step, we turn to IV regression to take into account the potential bias due to endogeneity, reverse causality and unobservables. As explained in Section 4, we employ a fully linear IV specification (Angrist and Krueger, 2001). Kelejian (1971) shows that the consistency of second-stage IV estimates does not depend on the functional form of the first IV stage. Angrist and Krueger (2001) further argue that predicted values computed from a non-linear first stage do not result in consistent estimates in the second IV stage, unless the non-linear model is exactly correct. Hence, we rely on linear specification and use the existence of a VET training license as an instrument for training activity, conditioning on the full set of controls.

The model statistics show that our instrument clearly fulfills the relevance criterion in all estimation models: training permission explains VET activities by 67.7% for every model as the relevance is independent of the type of innovation. The tests statistics for weak instruments – the Cragg-Donald Wald F statistic and Kleibergen-Paap Wald F statistic – vary between 4,922 and 6,279 in individual models. Since they are well above the critical values as proposed by Staiger and Stock (1997), we can reject the null hypothesis that our instrument has insufficient explanatory power to predict the endogenous variable. Conditioning the estimation on the full set of controls – including the investment in advanced equipment and qualified staff – we further assume that our instrument is conditionally independent of the outcome.

The results of the second-stage instrumental regression are reported in the middle panel of Table 4. Overall, we observe that the relevant coefficients in the IV models are comparable with those obtained in the LPMs based on balanced data, but they lose statistical significance. For all innovation measures aside from radical innovation, we observe marginal effects between 3.2% and 4.3%. However, a significant impact of initial VET can only be observed in the model for process innovation, which confirms the findings of Table 3. According to the IV estimates, the participation in the dual VET system leads to a 4.3% increase in the probability of reporting improvements of production or service processes. Thus, our results indicate that further research should devote even more attention to the potential effect of vocational training on DUI mode learning and process improvements. At the same time, the expectation of the minor importance of VET for radical innovations – which is already well established in the conceptual studies of VET – turns to be empirically well substantiated.

*5.3. Results for the subgroup of SMEs*

According to the conceptual literature (see Section 2) and the results reported by Rupietta and Backes-Gellner (2019), the effects of initial VET should be strongest for the subgroup of SMEs that often rely on DUI mode learning for innovation. Non-R&D-oriented DUI companies should profit most from the technology transfer and the knowledge diffusion stemming from vocational education institutions (Thomä, 2017). Hence, to test the hypothesis on the impact of initial VET on the innovativeness of SMEs (H4), we estimate the IV models for the subpopulation of companies with fewer than 250 employees (in accordance to the SME definition used by the European Commission). The first stage of the IV models again point to the fulfillment of the relevance criteria. The full set of results – including estimates on the control variables – is reported in the Appendix (Table A. 6).

Table 5. Results for small and medium-sized enterprises (SMEs)

| | **Regressions based on balanced data** | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| ***IV regression, 2nd stage*** | | | | | |
| Training company | 0.058** | 0.051* | 0.046** | 0.018 | 0.051* |
| $R^2$ | 0.183 | 0.182 | 0.144 | 0.087 | 0.181 |
| Adj. $R^2$ | 0.179 | 0.178 | 0.139 | 0.082 | 0.177 |
| ***IV regression, 1st stage*** | | | | | |
| VET training license | 0.685*** | 0.685*** | 0.685*** | 0.685*** | 0.685*** |
| Cragg-Donald Wald F statistic | 4,971 | 4,971 | 4,955 | 4,958 | 4,971 |
| Kleibergen-Paap rk Wald F statistic | 5,654 | 5,654 | 5,630 | 5,628 | 5,654 |
| Observations | 10,021 | 10,021 | 10,005 | 10,007 | 10,021 |

Notes: The table reports coefficients from instrumental variable regressions based on data weighted with maximum entropy weights. The results of the balancing procedure are given in the Online Appendix (Table A. 5). Dependent variables are indicators for innovation activity (general, product and process innovation, radical and incremental innovation). The set of controls includes all controls listed in Table 3 (firm size, indicators for the educational composition of a firm's workforce, indicators for a shortage of skilled workers, continuing training, R&D, investment and export activities, competition measures, demand expectation, broadband connection, state of technical equipment, indicators for foreign firms, family business, economic sector and sixteen federal states). The coefficient estimates for the control variables are reported in the Online Appendix (Table A. 6). Significance levels are denoted as: * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

The results of the estimations for the group of SMEs are given in Table 5. As postulated in hypothesis 4, we observe a positive impact of the participation in VET on the general innovativeness of SMEs. For all innovation outcomes – again with the exception of radical innovation – the estimated coefficients are positive and statistically significant. According to these results, SMEs' participation in the dual VET system leads to an increase in the probability of general innovation (5.8%), product innovation (5.1%), process innovation (4.6%) and incremental innovation (5.1%). Overall, the results of these models indicate that the innovative impact of VET is stronger for SMEs than for the total population of all business establishments (as reported in Table 4). The non-significant impact of VET on radical innovation is again strongly consistent with our hypothesis 2.

## 6. Conclusion and discussion

There is a substantial risk that innovation policy targeting R&D as the main source of economic progress will underestimate the role and transformative potential of economic agents not investing in internal R&D resources. The most recent innovation literature does not question the role of R&D in knowledge production, but it no longer regards R&D investments as "a sine-que-non" for innovation (Shefer and Frenkel, 2005). In proceeding beyond the linear model of innovation, corresponding studies stress the strong variety of R&D and non-R&D-based ways of learning in companies, which may lead to different kinds of innovation outcomes. In this context, special attention is paid to the role of locally-embedded tacit knowledge, the accumulation of experience-based know-how in day-to-day business processes and the importance of interactive learning among the entire workforce and between companies and external agents or institutions. In this literature, VET is increasingly acknowledged as an important driver of a mode of learning and innovation that extends beyond formal processes of R&D and science. In light of this, policy-makers who aim to foster innovation in less R&D-oriented knowledge environments or motivate companies to bridge the gap between R&D and production through innovation-related exchanges on the shop floor may consider the potential role of VET systems.

However, the empirical literature on the importance of VET for innovation still remains sparse and studies on the subject remain mostly conceptual. Overall, corresponding research argues that companies can profit from VET in terms of innovation for three different reasons. First, as vocational education leads to enhancing the skill and competence portfolio of employees, a VET trained production workforce will be more able to engage in incremental innovation. Second, going beyond the individual capability argument, the literature argues that initial VET activities incentivize companies to establish internal organizational structures and learning environments that facilitate the transfer of (tacit) knowledge within firms and are conducive for building up absorptive capacities at the organizational level of the firm. Third, the interaction with external VET education institutions may enable companies to get in touch with emerging technology trends and external knowledge inputs. For example, VET schools may serve as agents of knowledge diffusion regarding new technologies, and the continuous updating of VET curricula may support the transfer of specialized knowledge and new technologies from industrial leaders to less tech-savvy enterprises (which are often found in the SME sector).

Even if the arguments in favor of the positive impact of VET on innovation seem persuasive, there remains the threat that they can overvalue the factual impact of VET on innovation, at least for subsamples of different business establishments. In particular, huge manufacturers following the science-driven mode of innovation may treat training activity as crucial for quality considerations in manufacturing processes, but they may also lack the commitment to utilize the involvement in VET activities as a starting point for transforming their organizational innovation culture. By contrast, innovation stimuli stemming from VET education institutions can hold essential importance to low-tech companies that lack internal R&D resources (Alhusen and Bennat, 2020; Toner, 2010). Hence, there is a need for further empirical research to establish whether and for which types of enterprises participation in VET will result in superior innovation outcomes. This study directly addresses this research gap and provides empirical evidence on the role of VET for innovation.

We evaluate the impact of initial VET activities on innovation outcomes at the company level using highly reliable data of the German Employment Agency (the IAB EP dataset), which is a dataset that is representative for the whole population of German business establishments. To date, the empirical testing of the hypothesis on a positive link between initial VET and innovation is underdeveloped. To our knowledge, the pioneering study of Rupietta and Backes-Gellner (2019) was the first to provide some empirical evidence on this issue. Taking this as a starting point, we begin our analysis replicating the models estimated in the Swiss data of Rupietta and Backes-Gellner (2019). Here, we observe treatment effects of similar magnitude and direction as reported by the original study. In the second step, we extend the set of controls to examine the sensibility of the estimated coefficients to the inclusion of further important drivers of companies' innovation outcomes. In particular, we include indicators of R&D and continuing training, which were not included in the Swiss study. As expected, we observe a significant decrease in the measures of associations between initial VET and innovation outcomes. Finally, to improve the precision of the estimates, we employ a maximum EB procedure and use IV regression to account for problems associated with reverse causality, endogeneity of training decisions and potential omitted variable bias.

As a result, we observe that the effects of initial VET on innovation may be less robust than conceptually postulated. The participation in VET has virtually no effect on radical and product innovation. However, for the total business population of Germany, we observe a positive effect of VET activities on process innovation. Moreover, our results point to significant causal effects of VET on the general innovative capacities of SMEs.

Our results – which show the importance of initial VET for SME innovation – hold particular relevance for innovation policy. They imply that SMEs' participation in the VET system helps them to improve their skill and competence portfolio, establish structures conducive to organizational learning and strengthen their capacity to absorb technological knowledge from VET education institutions. In this case, promoting companies' engagement in the VET system should not only be regarded as a policy tool that aims to foster a smooth integration of youth into the regular labor market, but it can also serve as a measure of innovation policy for the SME sector. Similarly, the technological upgrade of vocational schools and training centers should not only be considered as a tool of modern education policy, but also as an integral part of (SME-oriented) innovation policy.

One further implication of our study refers to the measurement of innovation. Interestingly, expenditure on training is still not consequently incorporated into the standard sets of innovation indicators. Although the revisions of the Oslo Manual (OECD and Eurostat, 2005; OECD and Eurostat, 2018) reflect the growing appreciation of innovation sources besides R&D, they still seem to underestimate the role of VET for firm-level innovativeness. The most recent edition of the Oslo Manual (OECD and Eurostat, 2018) distinguishes "general training" from "training for innovation", implying that general skill enhancement of the production workforce does not result in any significant improvement of productivity or the innovative capacity of individual business establishments. Expenditure on initial VET (e.g. training of apprentices) is explicitly excluded as innovation-irrelevant investment (OECD and Eurostat, 2018). This reflects the prevailing conviction that production-related skill enhancement and organizational learning in manufacturing environments should be treated as the firm-specific, on-site qualification of low-skilled workforce (Dalitz and Toner, 2016; Hirsch-Kreinsen, 2008; Krueger and Kumar, 2004) without any relevance for innovation activities. The results of our study call such assumptions into question. Based on our results, the treatment of initial VET activities in methodological guidelines for innovation measurement may be thoroughly reconsidered.

Regarding future research, there is an ongoing need for further empirical research to establish whether and for which types of enterprises the participation in initial VET helps to facilitate organizational learning and results in superior innovation outcomes. Further progress in the understanding of the role of vocational training in innovation can be achieved by advancing and combining insights from quantitative research and qualitative methods. The latter can help to identify the potential mechanisms and channels of learning and knowledge transfer within initial VET, such as feedback and documentation systems (Barabasch and Keller, 2019). Following the blueprint of Figueiredo et al. (2020) – who examine learning processes in multinational subsidiaries – qualitative research could address the question of how VET participation can help to establish a vital learning environment at the company level. Quantitatively, the central challenge refers to improving the identification strategy. In this respect, it would be promising to examine the long-term innovation effects of initial VET activities based on panel data. For example, the effect of starting or stopping training activities on aggregate innovation outcomes could be analyzed as the quota of companies conducting vocational training varies over time (Seeber and Seifried, 2019). In addition, further research on the effect of changes in regulations or training schemes (e.g. the updating of VET curricula) on innovation activities could be a promising starting point to gain a better understanding of the link between initial VET and firm-level innovativeness. Hence, there remains a need and room for further research on the subject matter.

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**Appendix A**

Table A. 1. Baseline results, full set of results

| | Linear probability models | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| Training company | 0.078*** | 0.076*** | 0.050*** | 0.008 | 0.075*** |
| ***Controls*** | | | | | |
| Company size | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Share of unqualified workers | 0.015 | -0.002 | 0.048** | 0.015 | -0.003 |
| Share of qualified workers | 0.128*** | 0.108*** | 0.082*** | 0.043*** | 0.107*** |
| Share of university graduates | 0.413*** | 0.398*** | 0.237*** | 0.163*** | 0.388*** |
| Competitive pressure | 0.078*** | 0.078*** | 0.025** | -0.002 | 0.081*** |
| Demand expectation | 0.122*** | 0.117*** | 0.065*** | 0.040*** | 0.116*** |
| Foreign company | -0.028 | -0.027 | 0.015 | 0.006 | -0.028 |
| Shortage of skilled workers | 0.042*** | 0.044*** | 0.015 | 0.009 | 0.046** |
| Observations | 11,812 | 11,812 | 11,777 | 11,781 | 11,812 |
| $R^2$ | 0.103 | 0.103 | 0.064 | 0.044 | 0.101 |
| Adj. $R^2$ | 0.100 | 0.099 | 0.061 | 0.040 | 0.098 |

Notes: Further controls include indicators for economic sector and sixteen federal states.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Table A. 2. Extended estimation strategy with balanced data, full set of results

| | LPM balanced | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| Training company | 0.037*** | 0.039*** | 0.031*** | -0.000 | 0.040*** |
| ***Controls*** | | | | | |
| Company size | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 |
| Share of unqualified workers | -0.069 | -0.083* | 0.033 | 0.014 | -0.082* |
| Share of qualified workers | -0.047 | -0.067* | 0.029 | -0.000 | -0.065 |
| Share of university graduates | 0.151*** | 0.125** | 0.146** | 0.160*** | 0.130** |
| Competitive pressure | 0.068*** | 0.067*** | 0.024** | 0.010 | 0.067*** |
| Demand expectation | 0.082*** | 0.086*** | 0.050*** | 0.030*** | 0.083*** |
| Foreign company | -0.008 | -0.007 | -0.015 | -0.003 | -0.011 |
| Shortage of skilled workers | 0.045*** | 0.036** | 0.041*** | 0.011 | 0.033** |
| Continuing training | 0.083*** | 0.080*** | 0.041*** | 0.016* | 0.078*** |
| R&D activities | 0.266*** | 0.287*** | 0.236*** | 0.159*** | 0.286*** |
| Investment activities | 0.116*** | 0.109*** | 0.052*** | 0.019*** | 0.109*** |
| Technical state of equipment | 0.043*** | 0.042*** | 0.033*** | 0.019*** | 0.045*** |
| Export activities | 0.107*** | 0.103*** | 0.045** | 0.017 | 0.095*** |
| Broadband connection | 0.018 | 0.022 | -0.017 | 0.011 | 0.025* |
| Family business | -0.038* | -0.029 | -0.011 | 0.024* | -0.036* |
| Observations | 10,631 | 10,631 | 10,614 | 10,616 | 10,631 |
| $R^2$ | 0.215 | 0.211 | 0.162 | 0.094 | 0.206 |
| Adj. $R^2$ | 0.212 | 0.208 | 0.158 | 0.090 | 0.203 |

Notes: Further controls include indicators for economic sector and sixteen federal states.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Table A. 3. IV regression with extended control strategy, balanced data, full set of results

| | Instrumental variable regression | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| ***Second stage*** | | | | | |
| Training company | 0.035 | 0.032 | 0.043** | -0.012 | 0.037 |
| Company size | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 |
| Share of unqualified workers | -0.069 | -0.083* | 0.033 | 0.014 | -0.082* |
| Share of qualified workers | -0.047 | -0.067* | 0.029 | -0.000 | -0.065 |
| Share of university graduates | 0.151*** | 0.125*** | 0.146*** | 0.160*** | 0.130*** |
| Competitive pressure | 0.068*** | 0.067*** | 0.024* | 0.010 | 0.067*** |
| Demand expectation | 0.082*** | 0.086*** | 0.050*** | 0.030*** | 0.083*** |
| Foreign company | -0.008 | -0.007 | -0.015 | -0.003 | -0.011 |
| Shortage of skilled workers | 0.045*** | 0.036** | 0.041*** | 0.011 | 0.033** |
| Continuing training | 0.083*** | 0.080*** | 0.041*** | 0.016* | 0.078*** |
| R&D activities | 0.266*** | 0.287*** | 0.236*** | 0.159*** | 0.286*** |
| Investment activities | 0.116*** | 0.109*** | 0.052*** | 0.019** | 0.109*** |
| Technical state of equipment | 0.043*** | 0.042*** | 0.033*** | 0.019*** | 0.045*** |
| Export activities | 0.107*** | 0.103*** | 0.045** | 0.017 | 0.095*** |
| Broadband connection | 0.018 | 0.022 | -0.017 | 0.011 | 0.025* |
| Family business | -0.038* | -0.029 | -0.011 | 0.024* | -0.036* |
| ***First stage*** | | | | | |
| VET training license | 0.677*** | 0.677*** | 0.677*** | 0.677*** | 0.677*** |
| Company size | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| Share of unqualified workers | -0.107 | -0.107 | -0.108 | -0.108 | -0.107 |
| Share of qualified workers | -0.144*** | -0.144*** | -0.145*** | -0.145*** | -0.144*** |
| Share of university graduates | -0.133** | -0.133** | -0.136** | -0.136** | -0.133** |
| Competitive pressure | -0.006 | -0.006 | -0.006 | -0.006 | -0.006 |
| Demand expectation | -0.008 | -0.008 | -0.008 | -0.008 | -0.008 |
| Foreign company | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 |
| Shortage of skilled workers | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| Continuing training | -0.038*** | -0.038*** | -0.038*** | -0.038*** | -0.038*** |
| R&D activities | -0.002 | -0.002 | -0.001 | -0.001 | -0.001 |
| Investment activities | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 |
| Technical state of equipment | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 |
| Export activities | 0.011 | 0.011 | 0.011 | 0.011 | 0.011 |
| Broadband connection | -0.024 | -0.024 | -0.024 | -0.024 | -0.024 |
| Family business | -0.015 | -0.015 | -0.015 | -0.015 | -0.015 |
| Observations | 10,631 | 10,631 | 10,614 | 10,616 | 10,631 |
| $R^2$ | 0.215 | 0.211 | 0.162 | 0.094 | 0.206 |
| Adj. $R^2$ | 0.212 | 0.208 | 0.158 | 0.089 | 0.203 |

Notes: Further controls include indicators for economic sector and sixteen federal states

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Table A. 4. Results of the balancing procedure, all establishments

| | Treat | | | Control | | |
|---|---|---|---|---|---|---|
| | mean | variance | skewness | mean | variance | skewness |
| Company size | 150.10 | 18540855 | 39.38 | 150.00 | 486696 | 6.32 |
| Share of workers without vocational education | .16 | .05 | 1.62 | .16 | .06 | 1.58 |
| Share of qualified workers | .63 | .06 | -.81 | .63 | .07 | -.81 |
| Share of academics | .06 | .02 | 3.31 | .06 | .02 | 3.07 |
| Competitive pressure | .83 | | | .83 | | |
| Demand expectation | .33 | | | .33 | | |
| Foreign company | .07 | | | .07 | | |
| Shortage of skilled workers | .36 | | | .36 | | |
| Continuing training | .81 | | | .81 | | |
| R&D activities | .21 | | | .21 | | |
| Investment activities | .74 | | | .73 | | |
| Technical state of equipment | 2.82 | | | 2.82 | | |
| Export activities | .33 | | | .33 | | |
| Broadband connection | .81 | | | .81 | | |
| Family business | .73 | | | .73 | | |

Notes: Further balancing constraints include indicators for economic sector and sixteen federal states.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Table A. 5. Results of the balancing procedure, SMEs

| | Treat | | | Control | | |
|---|---|---|---|---|---|---|
| | mean | variance | skewness | mean | variance | skewness |
| Company size | 50.83 | 2904 | 1.60 | 50.80 | 4599 | 1.47 |
| Share of workers without vocational education | .15 | .05 | 1.69 | .15 | .06 | 1.70 |
| Share of qualified workers | .64 | .06 | -.85 | .64 | .07 | -.81 |
| Share of academics | .06 | .02 | 3.55 | .06 | .02 | 3.43 |
| Competitive pressure | .81 | | | .81 | | |
| Demand expectation | .32 | | | .32 | | |
| Foreign company | .06 | | | .06 | | |
| Lack of skilled workers | .35 | | | .35 | | |
| Further training | .79 | | | .79 | | |
| R&D activities | .17 | | | .17 | | |
| Investment activities | .71 | | | .71 | | |
| Technical state of equipment | 2.82 | | | 2.82 | | |
| Export activities | .29 | | | .29 | | |
| Broadband availability | .80 | | | .80 | | |
| Family business | .77 | | | .77 | | |

Notes: Further balancing constraints include indicators for economic sector and sixteen federal states.

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.

Table A. 6. Documentation IV-results SMEs with first and second stage based on balanced data

| | SME sector | | | | |
|---|---|---|---|---|---|
| | General innovation | Product innovation | Process innovation | Radical innovation | Incremental innovation |
| ***Second stage*** | | | | | |
| Training firm | 0.058** | 0.051* | 0.046** | 0.018 | 0.051* |
| Company size | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 |
| Share of unqualified workers | -0.079 | -0.098* | 0.011 | 0.007 | -0.103** |
| Share of qualified workers | -0.058 | -0.074* | 0.020 | 0.021 | -0.077* |
| Share of university graduates | 0.126** | 0.110* | 0.113* | 0.186*** | 0.116* |
| Competitive pressure | 0.066*** | 0.066*** | 0.019 | 0.001 | 0.065*** |
| Demand expectation | 0.073*** | 0.074*** | 0.036*** | 0.030*** | 0.074*** |
| Foreign company | -0.010 | -0.016 | -0.007 | -0.007 | -0.022 |
| Shortage of skilled workers | 0.059*** | 0.054*** | 0.034** | 0.007 | 0.050*** |
| Further training | 0.081*** | 0.078*** | 0.041*** | 0.007 | 0.076*** |
| R&D activities | 0.274*** | 0.283*** | 0.237*** | 0.141*** | 0.283*** |
| Investment activities | 0.116*** | 0.111*** | 0.038*** | 0.022*** | 0.109*** |
| Technical state of equipment | 0.036*** | 0.033*** | 0.041*** | 0.014** | 0.036*** |
| Export activities | 0.075*** | 0.072*** | 0.020 | 0.041*** | 0.064** |
| Broadband availability | 0.011 | 0.018 | -0.030** | 0.003 | 0.024 |
| Family business | -0.033 | -0.033 | -0.003 | 0.012 | -0.038 |
| ***First stage*** | | | | | |
| VET training license | 0.685*** | 0.685*** | 0.685*** | 0.685*** | 0.685*** |
| Company size | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Share of unqualified workers | -0.087* | -0.087* | -0.088* | -0.088* | -0.087* |
| Share of qualified workers | -0.112*** | -0.112*** | -0.112*** | -0.112*** | -0.112*** |
| Share of university graduates | -0.121* | -0.121* | -0.123* | -0.121* | -0.121* |
| Competitive pressure | -0.034** | -0.034** | -0.034** | -0.034** | -0.034** |
| Demand expectation | -0.035** | -0.033* | -0.033* | -0.033* | -0.033* |
| Foreign company | 0.015 | 0.015 | 0.015 | 0.015 | 0.015 |
| Lack of skilled workers | -0.014 | -0.014 | -0.013 | -0.013 | -0.014 |
| Further training | -0.048*** | -0.048*** | -0.047*** | -0.048*** | -0.048*** |
| R&D activities | 0.003 | 0.003 | 0.004 | 0.004 | 0.003 |
| Investment activities | -0.006 | -0.006 | -0.006 | -0.006 | -0.006 |
| Technical state of equipment | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| Export activities | 0.018 | 0.018 | 0.018 | 0.018 | 0.018 |
| Broadband availability | -0.020 | -0.020 | -0.020 | -0.020 | -0.020 |
| Family business | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| Observations | 10,021 | 10,021 | 10,005 | 10,007 | 10,021 |
| $R^2$ | 0.183 | 0.182 | 0.144 | 0.087 | 0.181 |
| Adj. $R^2$ | 0.179 | 0.178 | 0.139 | 0.082 | 0.177 |

Notes: Further controls include indicators for economic sector and sixteen federal states

Source: IAB Establishment Panel, Wave 2017. Data access was provided via remote data execution. DOI: 10.5164/IAB.IABBP9317.de.en.v1.