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

Eike Matthies [a,b], Katarzyna Haverkamp, Jörg Thomä [c, #], Kilian Bizer [b]

[a] *HAWK University of Applied Sciences and Arts, Faculty of Resource Management, Goettingen, Germany*

[b] *Chair for Economic Policy and SME Research. Georg-August-University of Goettingen, Germany*

[c] *Institute for Small Business Economics at the Georg-August-University Goettingen, Germany*

Abstract:

While an increasing number of conceptual studies postulate that vocational education and training (VET) activities have a positive impact on firm-level innovation, empirical evidence on the subject remains scarce. This study exploits establishment data from a representative survey of German companies to estimate the association between firms' participation in initial VET and their innovation outcomes. The results based on linear probability models and entropy balancing show that the relationship between VET activity and innovation are more ambiguous than often postulated. Overall, the participation in initial VET has virtually no effect on radical product innovation. However, a positive association between VET activities and incremental product innovation or process innovation is found in the case of microenterprises with fewer than 10 employees. From this, we conclude that participation in the VET system primarily promotes the innovation and learning conditions of very small training enterprises. The paper concludes with implications for policy and research.

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

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Corresponding author. joerg.thomae@wiwi.uni-goettingen.de

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 et al. 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 firm-level innovativeness (Lund and Karlsen 2020; Porto Gómez et al. 2018; Rodríguez-Soler and Icart 2018; Rupietta et al. 2021; Rupietta and Backes-Gellner 2019). The example of VET with its strong emphasis on person-embodied knowhow and experience-based learning therefore vividly illustrates how important tacit skills continue to be in the knowledge economy (Balconi 2002; Thomä 2017).

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 2021; Barabasch and Keller 2020; Hodge and Smith 2019; Lund and Karlsen 2020; Porto Gómez et al. 2018). These studies reveal that the following key dimensions of the a knowledge economy's competitiveness (see OECD 2004; Powell and Snellman 2004) are potentially fostered by conducting VET: knowledge diffusion, organizational learning and management innovation as well as the built-up of experience-base knowledge, which enables workers to contribute to complex problem-solving. Hence, firms in knowledge economies with strongly embedded VET systems such as Germany, Switzerland or Norway are expected to benefit from companies' VET activities in terms of innovation and competiveness (Cooke and Morgan 1994; Hirsch-Kreinsen 2008; Lund and Karlsen 2020; Porter 1991; Rupietta et al. 2021; Rupietta and Backes-Gellner 2019).

However, quantitative testing of the empirical relationship between initial VET and firm-level innovation remains scarce 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 this. We review and synthesize arguments in favor of the positive impact of VET on firm-level innovativeness and examine 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 seminal contribution of 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 correlations of increased 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 Swiss study and hence may induce omitted variable bias. As expected, we observe a sharp reduction in the measures of associations. For the purpose of robustness testing, we perform estimations based on entropy balancing.

Overall, our results indicate that the association of initial VET with firm-level innovation is more ambiguous than often postulated. For the total population of observed German companies, we find no effect of VET on radical innovation but a positive correlation between VET and incremental product innovation and process innovation. Since VET is often assumed to hold particular relevance for smaller enterprises (Alhusen and Bennat 2021; Porto Gómez et al. 2018; Rupietta and Backes-Gellner 2019; Thomä 2017), we also focus on the effects of VET on innovation for different firm size groups. The corresponding results imply that the association between initial VET and firm-level innovation is in fact strongest in the group of microenterprises with less than 10 employees.

On the one hand, our study thus corroborates the conclusions of previous research on the positive link between VET and innovation. However, we also show that this association is weaker than often postulated as it mainly holds only for the group of microenterprises. We therefore conclude that participation in the VET system increases the innovative capacity of very small firms in knowledge-based economies through organizational learning routines, knowledge diffusion and the built-up of tacit know-how. This finding holds certain implications for policy-makers. At present, innovation policy still tends to neglect non-R&D related sources of innovation such as VET (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; Kirner and Som 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; Thomä and Bizer 2013), 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 results therefore suggest that promoting a company's engagement in the VET system should not only be regarded by policy-makers as a tool to foster the smooth integration of youth into the regular labor market and secure a supply of skilled workers, but also as a measure of innovation policy towards the small enterprise 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 innovation policy in the knowledge economy.

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 arguments on the potential association between VET 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; Cohen and Levinthal 1989). Unsurprisingly, this research tradition did not assume that VET-based qualifications below academic levels holds much relevance for technological progress and firm-level 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; Pittaway et al. 2004; 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 learning by science, technology and innovation (STI) and is characterized by the production and use of explicit, codified and scientific knowledge. The second mode is based on learning by 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 flows, 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 internal 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 with DUI-mode learning constituting an important element of small firm innovation (see also Thomä and Zimmermann 2013; Runst and Thomä 2022). An essential prerequisite for DUI innovation in smaller firms to succeed – and thus a key starting point for policy support – is effective knowledge diffusion. On this basis, DUI-oriented SMEs often receive the necessary impetus to engage in innovation. Hence, measures to increase the capacity of smaller firms to absorb external knowledge by including a broad set of institutions that affect learning and innovation (particularity at the regional level), the integration of small and medium-sized enterprises (SMEs) in regional innovation systems and the upgrade workforce skills in SMEs to enable their participation in DUI mode innovation are vital in this context (Isaksen and Karlsen 2011; Hervás-Oliver et al. 2021; Hewitt-Dundas 2006; OECD 2010; Rammer et al. 2009; Thomä 2017; Bennat 2021). All of these mechanisms can be expected to be facilitated by the VET system (Brunet Icart and Rodríguez-Soler 2017; Hodge and Smith 2019; Lund and Karlsen 2020; Porto Gómez et al. 2018; Rupietta et al. 2021; Rupietta and Backes-Gellner 2019).

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 such as those occurring in the VET system are increasingly acknowledged as an essential element of DUI mode learning and innovation (Alhusen and Bennat 2021; 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; Deissinger 2012; Harris and Deissinger 2003; Pilz 2008; 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 smaller firms' absorptive capacities (Barabasch and Keller 2020; 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 (2020) 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 corresponding profession, along with its cultural values, ways of interacting and manufacturing standards by means of "learning-by-immersion". Alhusen and Bennat (2021) 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 (Lund and Karlsen 2020; 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 (Hodge and Smith 2019; Lund and Karlsen 2020; Porto Gómez et al. 2018; Rodríguez-Soler and Icart 2018; Rupietta et al. 2021; Rupietta and Backes-Gellner 2019). Hence, VET in knowledge economies such as Germany, Norway or Switzerland fosters knowledge dissemination and related innovation activities at the company level (Powell and Snellman 2004; Proeger 2020).

2.3. Empirical evidence

To our knowledge, Toner (2010) was the first 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 mode innovation). 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 programs, 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 studies of Porto Gómez et al. (2018) as well as Rodríguez-Soler and Icart (2018) and the Norwegian study of Lund and Karlsen (2020). 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. Rodríguez-Soler and Icart (2018) establish that geographical proximity is crucial for knowledge exchange networks between VET institutions and SMEs. In this way, VET institutions can be a driving force of regional innovation systems in terms of knowledge diffusion. Again, VET institutions are described as "a key node" (p. 13) in the knowledge network of DUI-oriented SMEs. Lund and Karlsen (2020) conduct nineteen in-depth, semi-structured interviews in two Norwegian manufacturing regions and re-establish the result of the Spanish studies, 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, the 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. Lund and Karlsen (2020) also illustrate this process, which is based on collaboration between VET institutions and industry actors, for manufacturing regions in Norway.

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. Synthesis: the potential impact of initial VET on innovation

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 organizational structures that strengthen the continuous inflow of new knowledge into training firms and foster a viable learning climate at the company level. At the same time, we expect several dimensions of the competitiveness of knowledge-based economies to be promoted through the VET system. These are knowledge diffusion, organizational learning and management innovation as well as the built-up of experience-based know-how. In sum, the innovativeness of training companies should therefore be higher than for non-participants. Moreover, the potential positive impact of initial VET on innovation should therefore result from a complementary relationship between a top-down approach (driven by management) and a bottom-up approach (driven by the trainees) to innovation in training firms (Hodge and Smith 2018).

Moreover, the skill enhancement associated with initial VET should result in incremental innovation rather than radical, market-shaping outcomes. In terms of product innovation, this should relate to minor changes and improvements to existing products. Something similar can be expected with regard to process innovation, where a firm’s involvement in initial VET can contribute to the continuous improvement, optimization and cost reduction of materials and components (Toner 2010). In this context, the empirical results of Rupietta and Backes-Gellner (2019) suggest that initial VET activities have a stronger impact on product innovation activities than for process innovation. Finally, the potential role of VET institutions – training centers as well as training curricula and their continuous updating – should be considered as well. Previous research further stresses their importance 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 smaller firms, which are not at the technological frontier of their industry and often lack necessary resources and competencies for technology sourcing.

3. Data

To investigate the link between VET and innovation, we use data from an extensive 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 firm size groups 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 et al. (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. The dataset includes information on 15,421 establishments, 43.5% of which report innovation outcomes and 45.6% 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. In contrast to their study, we also differentiate between radical and incremental product 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	0.43	0.50	0.53	0.50	0.35	0.48
Product innovation	1 if firm conducted product innovation	0.42	0.49	0.51	0.50	0.34	0.47
Process innovation	1 if firm conducted process innovation	0.16	0.37	0.22	0.41	0.11	0.31
Radical product innovation	1 if firm conducted new-to-market product innovations	0.07	0.26	0.09	0.29	0.06	0.23
Incremental product innovation	1 if firm conducted product innovation which is not new to the market	0.36	0.48	0.44	0.50	0.28	0.45
Explanatory variable							
Training company	1 if firm employs VET trainees	0.46	0.50	1.00	0.00	0.00	0.00
Control variables (step 1: replication)							
Company size	Total number of employees	114.30	858.34	215.06	1,257.90	29.81	110.03
Share of workers with vocational qualification	Employees with completed vocational training in total employment (%)	0.55	0.29	0.63	0.24	0.49	0.30
Share of workers with university degree	Employees with higher education in total employment (%)	0.09	0.18	0.09	0.16	0.08	0.19
Competitive pressure	1 for medium / substantial competitive pressure	0.69	0.46	0.74	0.44	0.66	0.47
Demand expectation	1 if company expects increasing business volume next year	0.26	0.44	0.30	0.46	0.24	0.43
Foreign company	1 if company is foreign owned	0.06	0.24	0.07	0.26	0.06	0.23
Shortage of skilled workers	1 if a company reports lack of skilled workers	0.25	0.43	0.34	0.47	0.17	0.38
Extended set of controls (step 2: further controls)							
Continuing training	1 if a company provides continuing training to their employees	0.67	0.47	0.86	0.35	0.51	0.50
R&D activities	1 if a company conducts in-house R&D	0.10	0.31	0.16	0.37	0.06	0.23
Investment activities	1 if a company made investments in 2016	0.61	0.49	0.74	0.44	0.50	0.50
Technical equipment	State of a company’s technical equipment (1 “state-of-the-art” – 4 “out of date”)	2.75	0.76	2.80	0.74	2.71	0.78
Export activities	1 for exporting companies	0.22	0.41	0.30	0.46	0.15	0.36
Broadband connection	1 if a company has high-speed internet access	0.78	0.41	0.83	0.38	0.74	0.44
Family business	1 if a company is family-controlled	0.77	0.42	0.67	0.47	0.84	0.37

Source: IAB Establishment Panel, Wave 2017. 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.

The underlying survey questions fully comply with the Oslo Manual guidelines on measuring firm-level innovation (OECD/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

[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*).

indicator for patent applications in our research setting. However, in contrast to Rupietta and Backes-Gellner (2019) we can control for a firm's R&D activity.

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 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 be associated with 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. To improve the precision of the estimates of the association between VET and innovation and to test for robustness of our results, we also perform estimations based on balanced data. We explain the motivation for the usage of the estimation strategy and the associated problems in more detail in the following section.

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 and Pischke 2008). In analogy to the Swiss study of Rupietta and Backes-Gellner (2019), we rely on LPMs rather than probit or logit models for consistency. 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 2008).

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. For the educational composition, we include information on the share of vocationally and academically trained employees. In contrast to Rupietta and Backes-Gellner (2019), we leave out an additional indicator for the share of unqualified workers due to collinearity. 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 (Hall and Jaffe 2018; Jensen et al. 2007). 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 in a robustness test. 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). EB generates weights so that specified moment conditions of covariate distributions of treatment and control group are balanced. The balancing reduces model dependency (Hainmueller 2012; Hainmueller and Xu 2013; Zhao and Percival 2017).

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 rather quickly, 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).

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 an 11.7% higher probability of being innovative than non-training companies. Thus, the point estimate in our estimation sample is five-percentage points higher than in the Swiss study, which reports a point estimate of 6.8%. Turning to product innovation, we observe a marginal effect of 0.116, which is again higher than the coefficient reported in the Swiss study (0.061). We further observe a positive association between initial VET activities and process innovation (0.072). 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 an overall positive association between initial VET and general firm-level innovativeness. The effect sizes and significance levels in the German sample are higher compared to those reported in the Swiss study. Moreover, we find some support for the argument that the association between initial VET and product innovation is stronger than in case of process innovation.

Table 2. Baseline results

	Linear probability models				
	General innovation	Product innovation	Process innovation	Radical product innovation	Incremental product 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	0.117***	0.116***	0.072***	0.025***	0.117***
R^2	0.144	0.141	0.095	0.053	0.148
Adj. R^2	0.141	0.138	0.092	0.049	0.145
Observations	11,764	11,766	11,769	11,773	11,764

Notes: The table displays marginal effects from linear probability models, 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 0.117). In case of radical innovation, the respective coefficient is lower (0.025). These results are consistent with the theoretical reasoning presented above, postulating a stronger correlation with incremental rather than radical product 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 innovation types, although they are much lower and partly not significant.

In particular, as expected, we cannot observe any positive impact of initial VET on radical product innovation, which is a result consistent with our theoretical reasoning. For the whole sample, we observe a positive relationship between VET and general innovation (3.1%***), product (3.0%***) and incremental product (2.2%**) as well as process innovation (2.7%***). Hence, based on an extended set of controls, we find evidence in favor our argumentation in Subsection 2.4. Additionally, the association between VET and product and process innovation are both significant with the former being stronger in comparison to process innovation, while Rupietta and Backes-Gellner (2019) do not observe an effect for 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. The knowledge associated with improvements in production and services processes thus often contains a relatively high degree of tacitness (Gopalakrishnan et al. 1999), which can explain the role of initial VET in this context. Moreover, by looking at the estimates differentiated by firm size, it can be seen that the significant effects for the whole sample are mainly due to microenterprises (Table 3). We observe higher and significant correlations only for companies with less than 10 employees while the coefficients are insignificant for companies with more employees. Hence, especially in very small firms, apprentices can play a crucial role in (incremental) innovation activities.

Table 3. Results of models with the extended control strategy differentiated by firm size

	Linear probability models																			
	General innovation				Product innovation				Radical product innovation				Incremental product innovation				Process innovation			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
Training company	0.031 ***	0.049 **	0.011	0.032	0.030 ***	0.049 ***	0.012	0.034	0.003	0.007	-0.002	0.003	0.022 **	0.037 **	0.002	0.018	0.027 ***	0.028 **	0.016	0.040 *
Controls																				
Company size	0.000	-0.004	0.001 *	0.000	0.000	-0.004	0.001 *	0.000	0.000	0.001	0.001 *	0.000	0.000	-0.002	0.001	0.000	0.000 ***	0.002	0.000	0.000 ***
Share qualified workers	0.031 *	0.043	0.060 *	0.020	0.023	0.036	0.054	0.012	0.008	-0.009	0.010	0.042	0.040 **	0.061 **	0.029	0.064	0.007	0.025	0.018	-0.033
Share of university graduates	0.159 ***	0.095	0.131 **	0.283 ***	0.155 ***	0.101 *	0.115 *	0.300 ***	0.098 ***	0.016	0.147 ***	0.119 **	0.177 ***	0.116 **	0.123 **	0.337 ***	0.080 ***	0.058	0.091 *	0.081
Shortage of skilled workers	0.041 ***	0.052 **	0.050 ***	0.016	0.036 ***	0.049 **	0.042 **	0.013	0.012 *	0.041 ***	-0.003	0.002	0.039 ***	0.048 **	0.038 **	0.021	0.035 ***	0.011	0.043 ***	0.039 **
Continuing training	0.094 ***	0.098 ***	0.084 ***	0.075 **	0.089 ***	0.093 ***	0.088 ***	0.058 *	0.012 **	0.016 **	0.007	0.007	0.081 ***	0.078 ***	0.086 ***	0.068 **	0.044 ***	0.042 ***	0.035 ***	0.081 ***
R&D activities	0.261 ***	0.320 ***	0.295 ***	0.209 ***	0.282 ***	0.330 ***	0.311 ***	0.239 ***	0.147 ***	0.181 ***	0.180 ***	0.115 ***	0.320 ***	0.362 ***	0.346 ***	0.266 ***	0.219 ***	0.297 ***	0.208 ***	0.187 ***
Investment activities	0.126 ***	0.120 ***	0.120 ***	0.162 ***	0.121 ***	0.115 ***	0.113 ***	0.165 ***	0.024 ***	0.029 ***	0.019 **	0.009	0.104 ***	0.093 ***	0.096 ***	0.152 ***	0.054 ***	0.052 ***	0.044 ***	0.090 ***
Technical equipment	0.045 ***	0.054 ***	0.041 ***	0.027 **	0.045 ***	0.054 ***	0.041 ***	0.029 **	0.011 ***	0.016 ***	0.003	0.010	0.047 ***	0.044 ***	0.060 ***	0.037 ***	0.030 ***	0.021 ***	0.024 ***	0.056 ***
Export activities	0.112 ***	0.183 ***	0.077 ***	0.072 ***	0.104 ***	0.171 ***	0.080 ***	0.059 **	0.024 ***	0.031 **	0.025 **	0.021	0.091 ***	0.120 ***	0.080 ***	0.060 **	0.052 ***	0.067 ***	0.053 ***	0.029
Competitive pressure	0.062 ***	0.055 ***	0.063 ***	0.085 ***	0.061 ***	0.055 ***	0.061 ***	0.096 ***	0.003	-0.006	0.012	0.028	0.051 ***	0.045 ***	0.045 **	0.095 ***	0.018 **	0.017 **	0.004	0.036
Demand expectation	0.072 ***	0.074 ***	0.075 ***	0.060 ***	0.070 ***	0.069 ***	0.073 ***	0.064 ***	0.025 ***	0.030 ***	0.029 ***	0.016	0.062 ***	0.060 ***	0.059 ***	0.070 ***	0.036 ***	0.031 ***	0.051 ***	0.022
Foreign company	-0.024	-0.041	-0.056	0.017	-0.027	-0.035	-0.064 *	0.007	0.003	-0.003	-0.046 **	0.040	-0.031 *	-0.019	-0.087 ***	-0.000	0.006	0.000	-0.032	0.036
Broadband	0.020 *	0.017	0.033 *	-0.009	0.022 **	0.014	0.038 *	0.005	0.007	0.005	0.013	-0.010	0.031 ***	0.040 ***	0.019	0.010	0.001	0.005	0.004	-0.020
Family business	-0.055 ***	-0.043	-0.064 ***	-0.034 *	-0.054 ***	-0.046	-0.062 ***	-0.039 **	-0.017 **	-0.044 **	0.000	-0.025 *	-0.064 ***	-0.031	-0.076 ***	-0.044 **	-0.024 **	0.005	-0.013	-0.033 *
Observations	10,581	4,757	3,402	2,422	10,582	4,758	3,402	2,422	10,586	4,762	3,401	2,423	10,581	4,759	3,399	2,423	10,584	4,761	3,400	2,423
R^2	0.217	0.142	0.195	0.226	0.215	0.141	0.193	0.232	0.083	0.079	0.100	0.075	0.230	0.139	0.197	0.243	0.149	0.119	0.114	0.135
Adj. R^2	0.214	0.133	0.184	0.211	0.211	0.132	0.182	0.217	0.079	0.069	0.088	0.057	0.227	0.130	0.186	0.228	0.145	0.110	0.102	0.118

Notes: The table displays marginal effects from linear probability models, estimated for different dependent variables (binary indicators for general, product, radical and incremental product, and process innovation) by company size classes (I: whole sample; II: 1-9 employees; III: 10-49 employees, IV: 50 or more employees). 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.

Hence, very small DUI mode firms should profit most from the knowledge diffusion stemming from vocational education institutions (on this issue, see Section 2). 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 (e.g. 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 a between 14.7% and 36.2% 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 would lead to overestimating the impact of initial VET activities on the innovativeness of individual companies.

5.3. Robustness test: results based on entropy balancing

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 training and non-training firms. The results of estimations based on balanced data are reported in Table 1 (for more details, see Table A.2 in the Appendix). In balanced LPMs, we obtain coefficients that are slightly higher than those estimated in the regressions reported in Table 4. We still do not observe any association between participation in initial VET and radical production innovation, which is again consistent with our theoretical reasoning. For all other innovation measures of innovation, we now observe significant associations between 3.0% and 3.9% for the whole sample. The coefficients for different firm size groups support the results reported in Table 3. After controlling for selection on observables, the results for the whole sample are again driven by a positive correlation between initial VET and innovation in microenterprises with less than 10 employees.

Overall, the results based on balanced data confirm that there is a positive association between initial VET and firm-level innovation. However, the observed associations are lower than those reported in the Swiss study of Rupietta and Backes-Gellner (2019) (Table 2). Moreover, it also shows that this effect applies only to incremental product and process innovations in very small firms with fewer than 10 employees.

Table 1. Results based on entropy balancing differentiated by firm size

	Linear probability models																			
	General innovation				Product innovation				Radical product innovation				Incremental product innovation				Process innovation			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
Training company	0.038***	0.048**	0.015	0.058*	0.039***	0.053**	0.014	0.067**	-0.002	0.005	-0.005	-0.007	0.033**	0.044**	0.009	0.043	0.030***	0.033**	0.014	0.042
Controls																				
Company size	-0.000	-0.008	0.000	-0.000	-0.000	-0.009*	0.000	-0.000	0.000	0.001	0.001	0.000	-0.000	-0.005	-0.000	-0.000	0.000	0.002	-0.000	0.000
Share qualified workers	0.008	0.031	0.069	-0.053	0.000	0.014	0.067	-0.048	-0.012	-0.015	-0.012	0.012	0.018	0.052	0.029	-0.001	0.001	0.029	0.024	-0.044
Share of university graduates	0.204***	0.093	0.276***	0.204***	0.195***	0.088	0.242***	0.232***	0.149***	0.119	0.214***	0.126	0.228***	0.143	0.236***	0.275***	0.116**	0.077	0.232***	0.016
Shortage of skilled workers	0.044***	0.070***	0.017	0.049**	0.034***	0.063**	0.010	0.034	0.012	0.049***	0.003	-0.004	0.033**	0.061**	0.000	0.040	0.044***	0.020	0.038*	0.058**
Continuing training	0.081***	0.106***	0.077***	0.010	0.077***	0.094***	0.087***	-0.005	0.016*	0.019*	0.012	-0.008	0.072***	0.079***	0.080***	0.033	0.047***	0.051***	0.030*	0.085***
R&D activities	0.264***	0.240***	0.298***	0.229***	0.295***	0.258***	0.317***	0.277***	0.171***	0.190***	0.203***	0.124***	0.335***	0.335***	0.359***	0.299***	0.224***	0.268***	0.196***	0.212***
Investment activities	0.115***	0.111***	0.106***	0.150***	0.109***	0.105***	0.098***	0.149***	0.020**	0.019*	0.007	0.032	0.100***	0.094***	0.085***	0.140***	0.052***	0.050***	0.036**	0.078**
Technical equipment	0.045***	0.061***	0.030**	0.036**	0.044***	0.062***	0.026*	0.037**	0.020***	0.028***	0.006	0.029**	0.051***	0.043***	0.054***	0.044***	0.034***	0.027***	0.020	0.059***
Export activities	0.103***	0.233***	0.082***	0.043	0.096***	0.220***	0.092***	0.019	0.011	0.040*	0.034**	-0.054	0.082***	0.174***	0.079***	0.024	0.046***	0.086***	0.060***	-0.010
Competitive pressure	0.070***	0.053***	0.041*	0.163***	0.069***	0.052***	0.041*	0.167***	0.012	0.002	0.009	0.055**	0.063***	0.046**	0.026	0.165***	0.027**	0.023	-0.017	0.096***
Demand expectation	0.076***	0.087***	0.088***	0.053**	0.079***	0.073***	0.091***	0.073***	0.028***	0.035**	0.046***	-0.003	0.069***	0.071***	0.066***	0.076***	0.048***	0.048***	0.068***	0.022
Foreign company	-0.001	0.006	-0.058	0.011	0.000	0.005	-0.057	0.012	0.010	0.012	-0.071***	0.058	-0.004	0.006	-0.061	0.006	-0.003	-0.037	-0.047	0.011
Broadband	0.018	0.032	0.045*	-0.043	0.022	0.030	0.047*	-0.033	0.010	0.006	0.012	0.002	0.028*	-0.006	0.032	-0.025	-0.018	0.056***	0.007	-0.062*
Family business	-0.052***	0.019	-0.058*	-0.071***	-0.043**	0.005	-0.047	-0.061**	0.015	-0.028	0.035*	0.003	-0.057***	0.011	-0.058*	-0.064**	-0.027	0.032	-0.004	-0.048*
Observations	10,581	4,757	3,402	2,422	10,582	4,758	3,402	2,422	10,586	4,762	3,401	2,423	10,581	4,759	3,399	2,423	10,584	4,761	3,400	2,423
R^2	0.213	0.157	0.201	0.257	0.211	0.155	0.200	0.261	0.095	0.108	0.153	0.089	0.232	0.159	0.200	0.272	0.154	0.152	0.134	0.158
Adj. R^2	0.209	0.147	0.190	0.247	0.208	0.144	0.189	0.247	0.092	0.099	0.142	0.070	0.229	0.151	0.189	0.257	0.151	0.144	0.122	0.142

Notes: The table displays marginal effects from linear probability models, estimated for different dependent variables (binary indicators for general, product, radical and incremental product, and process innovation) by company size classes (I: whole sample; II: 1-9 employees; III: 10-49 employees, IV: 50 or more employees). 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.

6. Conclusion and discussion

There is a risk that a R&D focused innovation policy 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 ongoing relevance of tacit skills and experience-based know-how under the conditions of the knowledge economy. 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 remains sparse and studies on the subject often remain conceptual. Overall, corresponding research argues that companies can profit from VET in terms of innovation for three different reasons, which in turn constitute fundamental aspects of a knowledge economy’s competitiveness: First, VET enhanced the skill and competence portfolio of employees; as a result, a VET trained production workforce will be more able to engage in incremental innovation. Second, going beyond the individual capability argument, initial VET activities incentivize companies to establish internal organizational structures and learning environments that facilitate the transfer of (tacit) knowledge within firms and are therefore conducive for building up absorptive capacities at the organizational level of the firm. Third, the interaction with external VET education institutions may enable companies (especially the very small ones) to get in touch with emerging technology trends and external knowledge inputs by fostering knowledge dissemination. 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 small business sector).

Even if the arguments in favor of the positive impact of VET on innovation seem persuasive, there remains the threat that they can overestimate the actual role of VET on firm-level innovation. For example, large manufacturing firms that follow 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 2021; 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.

To date, the empirical testing of the quantitative link between initial VET and innovation is underdeveloped. The Swiss study of Rupietta and Backes-Gellner (2019) was the first to provide empirical evidence on this issue. Taking this as a starting point, we begin our analysis replicating the models estimated by Rupietta and Backes-Gellner (2019). Here, we observe effects of similar direction but higher magnitude 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. 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 to account for problems associated with selection on observables.

As a result, we observe that the correlation between initial VET and innovation may be less robust than conceptually postulated. The participation in VET has virtually no effect on radical product innovation. For the total business population, we observe a positive effect of VET activities on incremental product innovation and process innovation. However, this effect is mainly due to microenterprises with fewer than 10 employees. We conclude from this finding that the knowledge diffusion function that the VET system has in knowledge economies (at least at the regional level) primarily holds relevance for the smallest of the training companies.

Our results holds some relevance for innovation policy. They imply that small firms’ 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 small enterprise 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 (small firm-oriented) innovation policy in knowledge-based economies.

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/Eurostat 2018; OECD and Statistical Office of the European Communities 2005) 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/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/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 is associated with superior innovation outcomes. Further progress in the understanding of the role of VET 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 2020; Hodge and Smith 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, as our empirical analysis does not allow to draw strict causal inferences. 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, it could be 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).

In this respect, it would be promising to examine the long-term innovation effects of initial VET activities based on panel data to control for such fixed effects or to apply an instrumental variable approach to cope with endogeneity. Moreover, 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 innovation. 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 product innovation	Incremental product innovation
Training company	0.117***	0.116***	0.072***	0.025***	0.107***
Controls					
Company size	0.000**	0.000**	0.000***	0.000	0.000**
Share of qualified workers	0.108***	0.096***	0.055***	0.024***	0.111***
Share of university graduates	0.490***	0.495***	0.254***	0.225***	0.513***
Competitive pressure	0.087***	0.085***	0.032**	0.011**	0.076***
Demand expectation	0.116***	0.114***	0.063***	0.036***	0.103***
Foreign company	0.029*	0.026	0.042***	0.025**	0.031*
Shortage of skilled workers	0.062***	0.056***	0.044***	0.017***	0.056***
Observations	11,764	11,766	11,769	11,773	11,764
R^2	0.144	0.141	0.095	0.053	0.148
Adj. R^2	0.141	0.138	0.092	0.049	0.145

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. Results of the balancing procedure, all establishments

	Treat			Control		
	mean	variance	skewness	mean	variance	skewness
Company size	149.9	1865789	39.29	149.7	480362	6.36
Share of qualified workers	.63	.06	-.81	.63	.07	-.82
Share of academics	.06	.02	3.31	.06	.02	3.06
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	.19			.19		
Investment activities	.73			.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.