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Abstract

In many European countries, firms engage heavily in the training of apprentices. The literature has investigated why firms provide such training, but almost no empirical evidence exists on how firms train and shape their apprentices' education outcomes. We investigate this question by estimating a training production function with employer-employee linked data on more than 3,700 Swiss firms and their 9,500 apprentices. Using measures derived from work psychology, we test whether apprentices are more likely to successfully complete training in standard time when they are trained in firms with better training processes. We find that apprentices are more successful in firms that assign tasks that make them find own solutions and that are more varied. We find only weak evidence for the hypothesis that the association of good training processes and education success is due to the assortative matching of good apprentices with good firms. We further show that our results are robust to different model specifications and formal sensitivity tests, suggesting an important role of firms and their training processes for apprentices' education success.

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1 Introduction

In many countries, firm-based apprenticeship systems are well-established institutions for providing non-college bound youth with vocational skills, thus enabling them to quickly integrate into the labor market (Kriesi et al., 2024). The key role of firms in these firms seems obvious, because apprentices spend most of their time during a training period of several years in firms, learning and working on the job. The economic literature has identified market conditions and institutional settings under which firms are willing to provide training (e.g. Leuven, 2005; Eichhorst et al., 2015). However, a prominent concern in the literature is that firms exploit apprentices as cheap labor (Wolter and Ryan, 2011). In line with this, surveys show that apprentices who experience a dropout often complain about the working and training conditions in their firm (Böhn and Deutscher, 2022). Accordingly, many institutional features of apprenticeship training such as external certification of training and standardization of curricula[1] have been interpreted as means of strengthening the provision and quality of training in firms.

Despite this interest in the provision of firm training and its institutional settings, the economic literature has so far not directly examined the quality of the training provided by firms and its effect on apprentices' outcomes. We contribute to the literature on firm training by addressing this gap and relating the training processes of firms to the learning outcomes of their apprentices. We first show that firms differ in how they train, i.e. what tasks they assign to apprentices and how they accompany them in the execution of these. Using measures based on work psychology, we show that the differences in training processes are associated with apprentices' education success. More specifically, apprentices in firms that allow them to find their own solutions and to work with diverse tasks have a lower likelihood of drop-out and a higher likelihood of success at final exams. A possible explanation is that high ability apprentices select into, or are recruited by, firms with high quality training processes. We show that several measures of apprentice and firm quality are positively, but only weakly correlated, suggesting a limited

[1] The economic literature has analyzed institutional features like the external certification of training and training outcomes (Acemoglu and Pischke, 2000), training curricula (Schweri et al., 2021), the fixed duration of apprenticeships (Malcomson et al., 2003), and external apprenticeship regulation more broadly (Dustmann and Schönberg, 2012).

role of assortative matching. This is in line with the absence of a work history for apprenticeship candidates, making it hard to observe their true ability.

Our results rely on a novel and rich data set, which combines a firm survey of about 3,700 Swiss training firms with administrative individual-level data of the 9,500 apprentices in these firms. The register data allow us to follow apprentices until the end of their training, i.e. to observe whether they have completed their training period without interruption and whether they have passed their exams. The merged data contain a large number of individual and firm characteristics that we use as control variables in estimating the effect of training processes on education success. While we do not claim causal identification in the absence of a corresponding research design, we address endogeneity concerns due to omitted variables by applying a recent contribution on formal sensitivity checks in the econometric literature (Cinelli and Hazlett, 2020). Our results prove robust to these checks and different model specifications.

We conclude that firms likely play an important role in promoting their apprentices' education success by reducing interruptions of training as well as permanent dropouts and exam failures.

The remainder of the paper is organized as follows. First, we provide key information on the role of firms in the Swiss apprenticeship system and the overall education success of Swiss apprentices. Then, we discuss the theoretical framework on the link between training processes and education success, followed by describing the data sources and estimation methods. In the next step, the main results, model extensions, and robustness analyses are presented before concluding with a brief discussion of the results and broader policy implications.

2 Apprenticeship training and graduation in Switzerland

Switzerland is particularly well-suited to examine the effects of firm-based training. In contrast to recent developments in other advanced dual VET-systems like Denmark and Germany, where a trend towards more general education can be detected, or in Austria, where the trend goes towards more full-time vocational schools, no such tendencies can be observed in Switzerland (Kriesi et al., 2022). Instead, more than half of its young population enters into a firm-based apprenticeship where the training firm is the major provider of education. Therefore, Swiss apprentices cover a very broad range of abilities and occupations, and due to their numbers, apprentices' success is of primary importance for the supply of skilled labor in the labor market.

While the well-known German apprenticeship system operates in a highly regulated labor market, the Swiss labor market is only lightly regulated (Muehlemann et al., 2010). Nonetheless, the vast majority of all training firms come from the private sector (FSO, 2024), provide training voluntarily and without state subsidies.

Training opportunities are advertised like normal vacancies and apprentices can apply to a large number of positions. The cantons, i.e. the Swiss states, supervise training firms and their ability to offer training with adequate quality. The adolescents can start applying to open positions after finishing compulsory schooling. After the two-sided selection processes between firms and adolescents, the apprentice (parents in case of minors) and the firm sign an apprenticeship contract, which is standardized except for a few (partly) variable aspects such as wage, holidays, and working hours. An apprentice spends 3 to 4 days a week in his or her training firm and most of the rest of the time in vocational school.

Apprenticeship programs exist for 250 different occupations with a fixed training period of 2 to 4 years. Each of the 250 programs has its nation-wide standardized curriculum. Part of the curriculum is a training plan that specifies the skills that are needed for passing the final exams. The standardization of curricula forces firms to train general skills next to firm-specific skills. Every curriculum is updated around every fifth year to accommodate labor market trends (Schweri et al., 2021). Firms are expected to offer training in all relevant tasks of the trade set out in the curricula. In turn, apprentices are expected to carry out these tasks, which they often practice by executing productive work for the firm.

However, not all apprentices complete the pre-defined training period without interruption. About one quarter of apprenticeship contracts are terminated prematurely, almost 50% of these terminations occur between the end of the probationary period and the first year (4-12 months) (FSO, 2023). Often, these premature contract terminations (PCT) do not entail a permanent dropout: 62% (74%) of all first-time apprentices re-enter an apprenticeship within one (two) year(s) of their first termination (FSO, 2023). Nonetheless, PCTs entail costs for both the firm and the apprentice, even though it is possible that the match between apprentice and the training firm or occupation improves after the PCT.

Towards the end of the apprenticeship period, apprentices take the final exam, which is defined by the curriculum, organized by the cantons, and graded by specially trained exam experts. If an apprentice fails the exam, she or he must wait one year before retaking it. Including repeaters, exam failures amount to 9%, whereas about 7% of all apprentices failed at their first attempt in the pre-Covid year[2].

After five and a half years, almost 90% of the apprentices in a cohort have successfully completed their training (FSO, 2023). Upon passing, the apprentice receives a certified national diploma and enters the job market or further education. More than 50% of apprentices who enter the labor market stay with their training firm directly after graduation (Mueller and Schweri, 2015).

Drop-outs who fail to complete an upper secondary education face significant economic consequences, as a diploma is highly valued in the Swiss labor market. Even if a dropout may enhance efficiency in some individual cases, reducing the total number of dropouts during training and the exam will improve the overall efficiency of the system for apprentices and firms alike. Therefore, we see the successful and timely completion of apprenticeships as a desirable outcome and use it as a dependent variable in the estimations to detect an association with the training processes in firms.

3 Theoretical framework

This section discusses how we conceptualize the effect of training quality in firms on apprentices' education success. As described in the previous chapter, the Swiss apprentice system uses instruments, such as national curricula and exams, in order to oblige firms in a specific occupation to train a defined set of general skills among

[2]The numbers in this paragraph are taken from the following files on the websites of the Federal Statistical Office for 2022: `https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/bildungsabschluesse/sekundarstufe-II/berufliche-grundbildung.assetdetail.24468966.html` and for 2019: `https://www.bfs.admin.ch/asset/de/12307128`.

the apprentices. Nonetheless, firms enjoy a great deal of leeway in training provision, which leads to variation in their training inputs that we exploit in the analyses. First, we explain firms' economic rationales for providing different training inputs and, secondly, use the idea of a training production function to explain the link between firms' inputs and apprentices' graduation success.

3.1 Firms provide varying training inputs

The training strategies and inputs of profit-maximizing firms are shaped by the characteristics of the markets in which they operate. Firstly, firms use different production technologies. With respect to training, their production process offers more or less work that can be well performed by apprentices (Wolter et al., 2006). Secondly, the decision on how much training to provide depends on the relative costs of hiring skilled workers from the labor market vs. training own skilled workers. Several studies have shown empirically that both the hiring costs for skilled workers (Blatter et al., 2012; Aepli et al., 2024) and the training costs (Muehlemann et al., 2007; Blatter et al., 2016) influence firms' provision of training.

The empirical literature on the costs of training builds on the classical human capital model of Becker (1964), who predicted that trainees, not firms, bear the costs of general training in competitive labor markets. In contrast, Acemoglu and Pischke (1998, 1999) discuss frictional labor markets with compressed wage structures that allow firms to earn rents on trained workers. Because these rents offset training costs, market frictions may induce firms to pay for general training. Both stylized models can explain the existence and functioning of apprenticeship systems. However, depending on the competition of the labor market, firms and apprentices bear different shares of the costs and returns for this training. Swiss firm-level surveys show that a large part of firms have net benefits from training already during the training period (Gehret et al., 2019). Hence, most firms provide training, but do not actually bear net costs because they can reap enough benefits from their apprentices' productive work to cover all training costs (i.e. the "production motive", Lindley, 1975). However, a substantial number of firms incur net costs during the training period (Gehret et al., 2019). These firms may later recoup their training investment by employing their apprentices and paying them below their marginal productivity ("investment motive"), exploiting the market power arising from market frictions. These firms are likely to provide more or better training inputs because they care about their future returns, which increase with the skills of their workers (Mohrenweiser and Backes-Gellner, 2010).

In addition to determining their own training inputs, firms also determine which apprentices to recruit. Apprentices' characteristics are also important training inputs. Because firms try to find apprentices that match well with their requirements and teams, and apprentices try to find a firm and occupation that match their preferences, firm-apprentice matches are unlikely to be completely random. This mirrors the situation in the general labor market, where an increasing literature discusses the presence of positive assortative matching (PAM) between workers and firms. Some studies find evidence for PAM (Abowd et al., 1999; Bonhomme et al., 2019; Card et al., 2013; Andrews et al., 2012). Abowd et al. (2018) finds PAM between sectors, but not between individual workers and firms within sectors. A recent overview article concluded that economic theory and evidence on PAM is "at best in its infancy" (Chade et al., 2017). However, the apprenticeship market differs from standard labor markets in ways that make PAM less likely: Young apprenticeship candidates have no or little labor market history that could reflect or signal their ability. Firms can only rely on easily observable aspects of their schooling history, such as education pathways and grades (which we can control for).[3] Likewise, candidates have little work experience and will find it difficult to form expectations about firm quality based on the limited information available. These considerations are in line with theories that interpret training as a screening mechanism. These models assume that firms need to observe young workers over an extended training period first to be able to identify apprentices' ability type (Acemoglu and Pischke, 1998; Mohrenweiser et al., 2020). Therefore, the scope for PAM of apprentices and firms already during the training period seems very limited.

[3] We are not aware of papers analyzing PAM on the apprenticeship market explicitly. However, a Swiss study found that the PISA test scores of first-year apprentices in eight of the largest Swiss employers did not deviate significantly from the scores of students in the last grade of the upper track in compulsory school (Moser, 2004). Thus, these top employers had not succeeded in recruiting apprentices with abilities above average.

3.2 Varying firm inputs and education success

In order to link firms' training inputs to apprentices' education outcomes, a "training production function" is a natural starting point, drawing on the idea of education production functions. These EPFs have been developed for studying the relationship of school inputs and student outputs and have been used extensively in educational economics[4]. However, learning technologies in schools and in firm-based apprenticeships are remarkably different (e.g., Billett, 2020; Kriesi et al., 2024). Schools typically use classroom instruction in age-homogeneous groups of about 20 to 30 students, in a situation protected from outside influences or demands. In contrast, apprentices are embedded in the productive work processes of their firm and in teams of employees of different ages and experience, with different roles and backgrounds. Explicit instruction, i.e. oral explanation, is only a small part of their on-the-job learning. Apprentices also observe the work of more experienced colleagues, try out and practice tasks with or without supervision. They receive feedback not from teachers, but from trainers, colleagues and often from customers and the work process itself (e.g. when something breaks). In summary, learning and working go hand in hand in apprenticeships. Therefore, typical inputs in EPFs such as teacher quality and school funding are not particularly helpful in setting up an adequate training production function.

Many of the variables used in the vocational literature originate from work psychology, particularly from the influential job characteristics model developed by Hackman and Oldham (1975) and Oldham and Hackman (2010). The model outlines the conditions necessary for workers to achieve high job satisfaction, strong performance, and intrinsic motivation. According to the model, these conditions are met when a worker experiences three "critical psychological states": a sense of the meaningfulness of the work, a feeling of responsibility for the outcomes, and awareness of the results of their work activities. The theory posits that these states are

[4]The literature is not fully conclusive, as e.g. Hanushek (2003) argues that inputs such as class size, teacher experience, and teacher education bear only a limited relationship to student outcomes. However, several researchers have found positive effects from different inputs, e.g. from reductions in class size (Angrist and Lavy, 1999; Krueger, 1999) and from the quality of teachers (Chetty et al., 2014). Moreover, the overall quality of schools (Hanushek et al., 2008; Chetty et al., 2011; Dale and Krueger, 2002; Deming et al., 2014; MacLeod et al., 2017; Altonji and Mansfield, 2018) and school funding (Lafortune et al., 2018; Jackson et al., 2015) show positive effects on student outcomes.

influenced by the presence of five core job dimensions. The first state, experienced meaningfulness, is shaped by three job dimensions: skill variety, task identity, and task significance. The second state, experienced responsibility, is driven by high autonomy. The third state, knowledge of results, is influenced by feedback. Numerous studies using this model have found positive correlations between these five dimensions and an individual's job satisfaction and motivation, along with negative correlations with job stress and turnover. (see Morgeson and Humphrey, 2006; Oldham and Hackman, 2010).

The more specific literature on dropouts and PCTs in apprenticeships also often draws on concepts from work psychology. While PCTs are clearly related to apprentices' personal characteristics, several studies find that apprentices identify the training and working conditions in their firms as one of the main reasons for their PCT (Schmid, 2010; Stalder and Schmid, 2016; Schuster, 2016). Indeed, some firm characteristics are correlated with the successful completion of apprenticeships (Rohrbach-Schmidt and Uhly, 2015).[5] Wenger et al. (2019) show that apprentices prefer that their trainers have good pedagogical skills compared to trade-specific and social skills. Several papers within educational science also build on the job characteristics model to study the effect of training processes on apprentices' dropout intentions (e.g. Negrini et al., 2016; Krötz and Deutscher, 2021, 2022). Negrini et al. (2016) finds that firms with the highest training quality, e.g. a high systematic use of training curricula, experience fewer PCTs. Furthermore, Krötz and Deutscher (2021, 2022) show a negative relationship between PCT intentions and giving feedback, offering a variety of tasks, work autonomy, as well as curriculum orientation. We will use similar survey items to capture training processes (see section 4.3).

Building on these theories and results, we thus include job and training quality variables[6] in a training production function. For each apprentice j in firm i and

[5] Rohrbach-Schmidt and Uhly (2016) use German firm-level data with self-reported firm PCT rates and find that firms that experience higher rates of PCTs are on average smaller and have no work councils. Christ (2013) uses an earlier wave of the same data and finds that firms that train apprentices with an investment motive are less likely to experience PCTs.

[6] In recent years, a significant number of publications on training quality have been published in the vocational literature, which has led to a wide range of definitions. These definitions differ regarding who uses the term and on the circumstances in which quality is invoked (Harvey and Green, 1993; Ebbinghaus et al., 2011). Quality indicators are often broken down into input, processes and outcome indicators, e.g. in the 3-P model of workplace learning. (Tynjälä, 2013, modified from Biggs (1999)). Guided by the 3-P model and previous literature, Böhn and Deutscher (2021) developed a detailed model of important characteristics and processes that affect

vocational school k, it takes the following form:

$$Y_{ijk} = f(Z_{ijk}, P_j, S_j, V_k, \phi_j, \epsilon_{ijk}), \qquad (1)$$

where different outcomes Y depend on apprentices' personal characteristics Z, firms' training processes P, further firm characteristics X, vocational school inputs S, the training occupation ϕ and random shocks ϵ. This function is part of the overall production technology that firms are subject to when maximizing their profits. Therefore, they will invest in training quality up to the point where their profits increase just as much as an additional unit of training costs. This depends on how much apprentices' productivity increases due to more training and on how much profit the firm can acquire from this increased productivity (see section 3.1).

The idea of the training production function can also be visualized. In Figure 1, we left out vocational schools, for which we have no data.

Figure 1

Figure shows the direction of the relationships between apprentice and firm characteristics, training processes, and the graduation outcome. Apprentice and firm characteristics and training processes are shown as variable groups, the figure contains only examples of the variables in these groups. Based on the figure, we also discuss econometric identification of the effect of training processes on education success and the variables used in the estimations in the next chapter.

4 Methods and data

4.1 Identification and estimation method

To estimate the effect of training processes in firms on apprentice's graduation success, we stipulate the following estimation model for the training production function:

apprentices' education outcomes. The model is classified into 30 different categories e.g. 13 process dimensions that affect eight output dimensions. In samples of commercial apprentices (Krötz and Deutscher, 2021, 2022) and cook and painter apprentices (Negrini et al., 2016), these training processes have been found to correlate with apprentices' dropout intentions.

$$Y_{ij}^* = \boldsymbol{P}_j\boldsymbol{\alpha} + \boldsymbol{X}_j\boldsymbol{\beta} + \boldsymbol{Z}_{ij}\boldsymbol{\delta} + \boldsymbol{\phi_j} + \boldsymbol{\epsilon}_{ij}. \tag{2}$$

The outcome Y^* of apprentice i in training firm j is a latent variable in our case, we observe graduation $Y = 1[Y^* > 0]$. The outcome variable depends on the vectors of training processes $\boldsymbol{P}$, firm characteristics $\boldsymbol{X}$, apprentices' personal characteristics $\boldsymbol{Z}$, and the training occupation $\boldsymbol{\phi}$. Unobserved influences are captured by the stochastic error term $\boldsymbol{\epsilon}$. We are interested in the vector $\boldsymbol{\alpha}$ which captures the effect of training processes on graduation.

However, it is unlikely that the classical assumptions for causal interpretation hold. Interpreting Figure 1 as a Directed Acyclic Graph (DAG) (e.g. Pearl, 2018)[7], the arrows show the causal paths between the different variable groups (nodes). In particular, the arrow pointing from processes to outcome is the effect that we would like to identify. However, as the figure suggests, there are back-door paths from processes to outcomes operating via apprentice and firm characteristics. There are two main back-door paths that need to be closed to measure the causal effect of training processes on graduation. Firstly, there is an open path (path A) if unobserved firm characteristics (indicated as a grey area in the figure) are correlated with both training processes and the outcome. An example of this is if some firms have a higher quality of management than others. If this improves apprentices' outcomes and these firms also differ in their training processes, training processes and graduation success will be (spuriously) correlated.[8] The estimation would thus suffer from the classical omitted variables problem. Hence, we use the extensive information on firms from the firm survey in the estimations to alleviate this problem.

Secondly, there is a back-door path (path B) if unobserved apprentices' inputs are correlated with the training processes and the outcomes. The leading example

[7] Heckman and Pinto (2024) discuss the application of the DAG framework to questions of econometric causality. They criticize that the assumptions of certain research designs such as instrumental variables cannot be accommodated in this approach. In contrast, we think that the DAG representation is helpful for discussing the challenges related to (un)observable variables in our paper.

[8] Of course, it is difficult to distinguish between confounder and cause in practice in this setting. One might argue that everything about a training firm that influences graduation should be counted as "training quality". In this case, the research question is whether firms matter for apprentices' education success. We look at the more specific question of the effect of certain training processes, which we describe in the data section. The distinction is important for policy conclusions, i.e. whether improving these training processes in firms would increase apprentices' success.

is apprentices' unobserved ability, which influences outcomes. In the case of positive assortative matching between apprentices and firms, their ability will also be correlated with training processes. In section 3.1, we argued why PAM is likely limited in apprenticeships. Firms use readily available information from CVs in application processes to assess apprentices' abilities, such as education history and grades, and collect information using assessment tests. Therefore, we assume that any assortative matching is driven by observable information on apprentices and that controlling for this information will block the back-door path, i.e. remove endogeneity concerns due to assortative matching.

Thus, considering Figure 1 and the distinction between observed and unobserved variables, equation (2) can be rewritten as:

$$Y_{ij}^{*} = \boldsymbol{P}_j \boldsymbol{\alpha} + [\boldsymbol{X}_j \boldsymbol{\beta} + \boldsymbol{X}_j^U \boldsymbol{\beta}^U] + [\boldsymbol{Z}_{ij} \boldsymbol{\delta} + \boldsymbol{Z}_{ij}^U \boldsymbol{\delta}^U] + \boldsymbol{\epsilon}_{ij}, \tag{3}$$

where $\boldsymbol{X}_j$ and $\boldsymbol{Z}_{ij}$ are observed by the econometrician and $\boldsymbol{X}_j^U$ and $\boldsymbol{Z}_{ij}^U$ are unobserved. Firstly, there are potential omitted variables $\boldsymbol{X}_j^U$ that are correlated with $\boldsymbol{P}_j$ and the outcome Y_{ij}^{*}. Omitted variables will produce biased estimates if the standard assumption that the error term has a mean of zero conditional on observed variables is not fulfilled. Secondly, if assortative matching happens, firm averages of $\boldsymbol{Z}_{ij}^U$ vary across j, are correlated with $\boldsymbol{P}_j$, and $\boldsymbol{\delta}^U \neq 0$. If $\boldsymbol{X}_j^U$ and $\boldsymbol{P}_j$ are positively correlated and/or there is PAM, the estimated effects from equation (2) are biased upwards. Ideally, we would exploit a (quasi-)experimental design in which apprentices are randomly allocated to different firms. However, we are not aware of a credible source of randomness in the allocation of apprentices to firms that would not affect their success during apprenticeship. Instead, our strategy is to control for variables that capture this allocation, which may be more promising than it first appears. Altonji and Mansfield (2018) show that using averages of observables to control for sorting on unobservables at a higher level of aggregation, in our case at the firm level, can be sufficient in a setting similar to ours under certain circumstances.[9] An important difference is that sorting on unobservables is likely limited in our setting (see section 3.1), but controlling for firm means of individual

[9]Our equation 3 is inspired by their paper, which studies the sorting of students to certain schools in certain neighborhoods. While this is a one-sided selection problem. the matching of firms and apprentices is two-sided.

characteristics contributes to removing any bias due to assortative matching.

Hence, based on previous discussions we need (in addition to fixed effects for training occupations and entry cohorts):

- individual characteristics to control for (observable) differences in ability, $\boldsymbol{Z}_i$, and
- firm characteristics to control for the choice of training processes and for the attractiveness of the firm $\boldsymbol{X}_j$.
- firm means of the characteristics of their apprentices to control for average ability due to the matching process $\boldsymbol{Z}_j$.

We assume that the selection of training processes and matching take place on the basis of observable variables $\boldsymbol{Q_{ij}} = [\boldsymbol{Z_i}, \boldsymbol{Z_j}, \boldsymbol{X_j}]$. This means that conditioning on the observables $\boldsymbol{Q_{ij}}$ is sufficient to control for endogenous training firm processes. This can be expressed as:

$$Y_{ij}^* = \boldsymbol{P}_j \boldsymbol{\alpha} + \boldsymbol{Q}_{ij} \boldsymbol{\zeta} + \boldsymbol{v}_{ij}, \tag{4}$$

where $\boldsymbol{\alpha}$ are the coefficients of interests and we assume that individuals who are the same in the observable dimension $\boldsymbol{Q_{ij}}$ but attend different values of $\boldsymbol{P}_j$ do not differ, on average, in the unobservable dimension $\boldsymbol{v}_{ij}$.

By definition, the claim that unobservables do not matter cannot be tested directly. However, in order to address the issue of a possible bias due to omitted variables, we estimate a number of robustness checks to increase our confidence in the results. We provide an explicit sensitivity analysis following Cinelli and Hazlett (2020). The premise of the sensitivity analysis is to evaluate the potential importance of unobservable variables $\boldsymbol{X}_j^U$ and $\boldsymbol{Z}_{ij}^U$. This is done using a 'benchmarking' practice, which assesses the strength the unobservable variables would need to have to reverse the estimated effect, by comparing them with the association strength of observed variables.

We use linear probability models in the estimations with binary outcome variables, such as education success. Apprentices are the unit of observation in most models, with standard errors that account for clustering at the firm level. Results using Probit regressions are very similar to the results with linear probability models (delivered on request). In the estimations, we start with parsimonious estimation models and add further control variables step by step. We will use three groups of variables in addition to basic controls: apprentice characteristics, firm characteristics, and controls intended to reflect assortative matching between firms and apprentices. This procedure allows the reader to assess the results with more or less controls.[10]

4.2 Linked survey and register data

To investigate the effect of different training processes, we use a novel data set of 9,538 (20,583) apprentices in 3,792 Swiss training firms in the main (extended) sample, which comes from two data sources.

The fourth Swiss survey on costs and benefits of training firms (CBS) surveyed Swiss firms about their training activities, the costs and benefits of training, the recruitment of apprentices and skilled workers, and many firm characteristics and processes (Gehret et al., 2019). The online survey was conducted in spring 2017, using a random sample from the Swiss firm register, stratified by training occupations and firm size. The firms were asked about their training in the training year 2016/17. For firms with more than one training occupation, one was chosen randomly before the survey was sent out. Hence, the survey measures training activities for a firm and occupation dyad.

This firm-level data has been merged with administrative data on education histories from the Swiss Federal Statistical Office (FSO).[11] The longitudinal analyses of education and training (LABB) includes the full population of individuals in the education system in Switzerland. It thus covers every student's and apprentice's education spells since 2011. The data has only been recently made available by FSO, which uses it to analyze descriptive indicators and developments in the Swiss education system (PCT rates; e.g FSO, 2019). Hence, the data contains information about the educational success of apprentices and the schooling they experienced

[10] Note that these three groups of variables do not fully coincide with the matrices discussed above, because we want to show the effect for matching controls separately, which include firm variables in addition to firm means of individual characteristics.

[11] Cost-benefit surveys have been merged with register data on individual labor market histories in Germany, e.g. Rohrbach-Schmidt and Uhly (2015); Dietrich et al. (2016). In their working paper, Dietrich et al. (2016) find a positive relationship between the total cost of apprenticeship and the post-training wage of the apprentices.

before entering the apprenticeship system.

From the originally 5,704 firms sampled, 99 firm identifiers were not identified in the LABB data set. A few more firms were excluded due to inconsistencies between the data sets.[12] Hence, the sample was reduced to 5,585 firms with a total of 88,558 apprentices. However, because the CBS survey collects information on firm-occupation dyads, the sample is reduced by 44'481 apprentices who are trained in an occupation different from the chosen one. Training processes vary by occupation, therefore we want to rely on within occupation variation only and include occupation-fixed effects in all estimations. We include apprentices from the 40 most frequent training occupations in the sample and drop those who train in small occupations (8,553). This resulted in a large sample of 35,524 apprentices used to calculate the firm mean of apprentice characteristics.

To define the main and extended samples, we excluded 9,958 apprentices, who started their apprenticeship contracts before 2011, as we can only observe PCTs from 2011 onward, or belong to later entry cohorts whose education duration prevents us from having information on their graduation outcomes. We also restricted the sample to include only apprentices who entered the firm in their first year of apprenticeship in the case that they had an earlier contract at another firm (and thus a PCT). We excluded cases with missing values for the dependent or main independent variables from either the survey or the register data, accounting for 8% of the sample.

Finally, to define the main sample from the extended sample, we excluded apprentices who were not in the training firm at the time the CBS survey took place. However, we included those apprentices who should have been at a CBS firm if they had not had a PCT before the survey took place.

The final main sample consists of 9,538 apprentices in 3,792 different firms. If we are willing to assume that the information on firms collected in the survey is valid for periods before and after, we can include additional apprentices in these firms who were present before and after the survey date. We use this extended sample to compare the results of our main estimation specification between the main sample and the extended sample

[12] For some firms in CBS, there were no apprentices (between 2011-2020) according to LABB. Probably, the respondents in the survey had answered for a different firm ID.

4.3 Variable selection

In the analyses, we regress the outcome 'education success' on the main variables of interest, i.e. the items reflecting firms' training processes, and several sets of control variables.

As the summary statistics in Table 1 show, 78% of all apprentices complete training in standard time and pass the exam successfully. Among the 22% who do not succeed according to this definition, 17% experienced a PCT during their apprenticeship and an additional 5% failed in their first attempt at the final exam.[13]

The information for the 'graduation success' variable comes from the register data that tracks every apprenticeship contract in Switzerland, including information on graduation status, premature contract terminations, and final exam passing. The variable is coded with the value one if there was no PCT during the individual's first apprenticeship period and the apprentice passed the final exam at the first trial.

The CBS questionnaire included detailed questions about firms' training processes and organization. We build on the work psychology and vocational literature (section 3.2) and use questionnaire items that were found to be useful measures for the quality of firm training (Negrini et al., 2016). Respondents rated seven questions about training processes such as 'I plan training units in advance' and 'I make sure that the apprentices get varied tasks' on a scale of 1 to 7 (applies not at all - fully applies).[14] These variables reflect four dimensions of training quality, namely the planning of training, the support of elaboration and self-regulation, cognitive activation, and feedback, following Negrini et al. (2016). Not surprisingly, these authors found that trainers in Swiss firms reported significantly higher scores than apprentices, but the scores were highly correlated. On average, firms in our sample report a relatively high average score between 5.5 and 5.92 for the seven items (see Table 1). The variance is limited seeing the 7 point scale, because values below 4 are reported rarely, resulting in standard deviations of slightly more than unity. The items can be seen as (1) measures capturing one dimension, namely training

[13]Note that the rate of exam failure (5%) is lower than the one reported by official statistics (9%) reported in section 2 because the latter includes apprentices that repeat the exam.

[14]Translated from German, the other five process items are: 'I agree on learning objectives with the apprentices', 'I give assignments and tasks which the apprentices can work/practice on autonomously', 'I let the apprentices find their own solutions', 'I give apprentices feedback on their work regularly', 'the apprentices get insights into all phases of the production process'.

quality, or (2) capturing several dimensions (as Negrini et al. (2016) do), or (3) as separate, even if correlated training processes. We are agnostic about the exact relationship between the processes and items a priori, therefore we prefer a 'let the data speak' approach, i.e. we use the seven items as independent variables. However, we will also show results when we extract the first principal component from the seven items as an overall measure of training quality, which conforms to view (1).

In addition, the linked survey and register data contain ample information on apprentices and firms that we add as controls in the estimations. We do this step by step, organizing control variables into four sets of variables: basic controls, individual apprentice characteristics, firm characteristics, and variables with a focus on the matching between apprentices and firms.

Cohort and occupation fixed effects are included as basic controls in all estimations. The largest single occupation is 'commercial employee' containing 1'458 apprentices and the smallest occupation is 'assistant in hospitality services' with 40 apprentices.

Information on individual apprentices include gender, immigration status, and apprenticeship starting age (seven categories). Ability-related variables are whether apprentices study for a vocational baccalaureate during their apprenticeship, which is a degree enabling them to study at a University of Applied Sciences later; whether they attended a transition or bridge course after lower secondary school to get into upper secondary education, which indicates difficulties in the transition; and whether they attended the advanced track in lower secondary school. Vocational baccalaureate and advanced track indicate higher ability, a transition course lower ability.

Firm characteristics include region (seven greater regions, defined by FSO), sector (four categories), and firm size (four categories). From the CBS survey, we use respondents' assessment on three questions: whether the firm has personnel problems, a high innovation ability, and a high efficiency in processes. These variables have been recoded as dummy variables, 1 indicating agreement with the item. Finally, we include the salaries paid to apprentices and skilled workers.

To control more specifically for assortative matching, we include additional variables related to the sorting of firms and apprentices and the application process. These include: the log of the number of applicants for apprenticeship positions, whether the firm uses an assessment test to screen apprenticeship candidates, and the first principal component of apprentices' mean grades at firm level in math, first, and second language in lower secondary school. In addition, we control for firm-level means of individual characteristics by aggregating these over all apprentices in the firm (akin to the approach by Altonji and Mansfield (2018), see previous section). For each firm, We thus calculate the percentage of apprentices that are female, born in Switzerland, attend vocational baccalaureate courses, did a transition course from lower to upper secondary education, attended the advanced track in lower secondary school, and the mean of apprentices' age.

Table 1

Additionally, the survey includes further information on training organization and practices, e.g. if and what kind of training plan is used and how much time resources the trainer has for training. We look at these training variables in the extensions of our main results.

5 Results

The focus of our main analysis is on firms' training processes and their relationship with apprentices' graduation. In a further section, we extend the analysis by investigating different aspects of successfully completing training. Finally, we use formal sensitivity analyses to discuss how sensitive our main results are to the endogeneity concerns discussed in chapter 4.1.

5.1 Training processes in firms

In the survey, firms gave relatively high self-assessments on the quality of their training processes. The means of the seven training process items are shown in Table 1 and the full distribution of firms' answers in Appendix Figure A5. These distributions are all skewed to the right with very few firms showing values below three. However, there is substantial variation between firms with approximately 25-40% of the firms indicating the highest value (7) and 55-70% indicating values between 4 and 6. Not surprisingly, the training processes are all correlated positively among each other, with correlation coefficients ranging from .27 to .62 (shown in Appendix Figure A6).

Firms decide about their training processes based on their production processes and training motives (see section 3.1). For a better understanding of the relationship between training processes and firm characteristics, we first regress each training process item on firm variables. Table 2 shows these firm-level regressions.

Table 2

Public and non-profit firms do more planning for their training, but give their apprentices fewer opportunities to work on tasks autonomously. Larger firms also do more planning, but provide apprentices less insights into their production processes, probably because production processes are more complex and the division of labor is more pronounced in larger firms. Firms with more efficient processes and with higher innovation ability also score higher in the training process items, as do firms that use assessment tests in recruiting apprentices. Among the characteristics of firms' apprentices, their grades stand out: Apprentices with higher grades are more often found in firms with better training processes.

5.2 Training processes and education success

Our main interest is in the effect of the training processes on apprentices' education success. In order to provide the full picture on all items, Figure 2 shows the point estimates of the regression coefficients for the respective item, each based on a separate linear probability model. For each training process, we show the basic specification and three further specifications, which add sets of control variables on apprentices, firms, and matching indicators step by step (see section 4.3). The lines show the the 95% confidence interval around the point estimate.

Figure 2

The figure shows that two training processes are positively and significantly associated with successful training completion in all model specifications: giving apprentices tasks that allow them to find their own solutions and giving them a large variety of tasks. The other training processes, which pertain to letting them work autonomously, learning objectives, planning, giving feedback and providing insights in the full production process, all show a positive relationship with graduation as well. Yet, adding control variables makes these point estimates insignificant at the conventional 5% level, if only narrowly in some cases.

Because the processes are correlated among each other, we also ran regressions with all items in one model (Appendix Table A2). The process items are jointly significant in an F-test. Interestingly, the two items *own solutions* and *varied work* still emerge as significant with only slightly reduced coefficients, suggesting that they are important aspects of firms' training quality. Finally, in order to study a common quality factor emanating from the seven items, we can extract the first principal component (FPC) of the seven process items. As the lowest part of Figure 2 shows, the FPC coefficients are also positive and significant in all models.

The significant coefficients in our main specifications in Figure 2 are around .02. This appears to be a high effect size, given the seven-point scale of the items. However, because the standard deviations are only slightly higher than one scale point, education success becomes more likely by slightly more than 2 percentage points if the corresponding training process variable increases by one standard deviation. If causal, this is still a substantial effect: it means a 10 percent reduction in education failure, because the rate of failure is at 22 percent in our sample. In the model containing all items, the combined effect of the two significant variables (last column of Appendix Table A2) even amounts to over 3 percentage points or 15 percent increase in educational success for quality increases by one standard deviation.

The causality of these estimates hinges on making sure that the influence of unobserved variables on the results is very small. We argue that our observed control variables capture confounding influences to a large extent (section 4.1), therefore we show the regression coefficients of the control variables in Table 3 in a model with the process item *varied work*[15].

[15] Using any other training process changes the point estimates for the control variables only marginally.

Table 3

Individual variables reflecting higher ability are positively related to education success in model 2 in Table 3, namely apprentices attending vocational baccalaureate school during the training period and those having attended the advanced track in lower-secondary school. Apprentices are also more likely to succeed in larger firms, in firms with more efficient management, and such that pay higher salaries to skilled workers. We will use and discuss the results of models 3 to 5 in Table 3 in the further subsections.

In summary, the results of our empirical analysis so far suggest that training processes are important determinants of graduation. The two dimensions of training processes that stand out are *varied work* and *own solutions*. Before we probe these results by looking at the role of assortative matching and by applying sensitivity checks, we take a closer look at the effects of training processes on the two dimensions of education success.

5.3 Training conditions in firms

Our focus is on the processes between trainers and apprentices, but these training processes are shaped by the frame that the firms provide for trainers and apprentices. First, trainers are mostly senior collaborators who train apprentices part-time, i.e. next to their further duties. Thus, it likely matters how much time they have at their disposal to provide training. A recent survey suggests that this is the foremost concern of trainers in Swiss firms (Wenger and Lamamra, 2023). Secondly, it might also matter what apprentices do in the limited time they spend in firms. Firms can give them tasks that unskilled workers could perform, or more challenging work that skilled workers usually do. The latter tasks are likely to lead to better learning outcomes. Thirdly, firms get some support in training from professional associations, which provide them with training plans that facilitate planning. Some firms also develop their own plans as a foundation for their training processes.

All of these aspects are correlated with good training processes, as Appendix Table A3 shows. Trainers' time resources, the share of skilled work apprentices do, and the use of training plans, are all associated significantly with higher training process quality, e.g. with the first principal component (last column). Therefore, we also check whether controlling for these variables in our main regressions reduces the coefficients of the training process items. Interestingly, the coefficients for *own solutions* and *varied work* are hardly influenced (see Appendix Figure A7). This finding suggests that good conditions for training in firms, like enough time for trainers, mainly increase the quality of training processes, which in turn increase apprentices' education success.

5.4 Effect heterogeneity

Above, we defined education success as completing the training period in standard time and successfully passing the final exam. However, training processes may have different effects on the two events precluding graduation, namely exam failure and PCTs. Apprentices may decide to terminate a contract for reasons that are unrelated to the overall training quality. For example, they may drop out of the current training program and change occupation (FSO, 2019; Wydra-Somaggio, 2021) because their preferences for occupations may have changed since starting training. However, we would expect firm training quality to affect other drop-outs, e.g. when apprentices do not enter a new education or a less demanding one, and exam success, because vocational skills are tested at the exams.

In panel (A) of figure 3, we use the dependent variable *Exam success*, which indicates whether an apprentice, who attained the exam without PCT, was successful or failed at the final exam. While absolute coefficient sizes are smaller due to a smaller baseline (the exam success mean is at .95), the same two process variables show positive and significant coefficients in all model specifications. Panel (B) uses *No PCT* as the dependent variable, which indicates whether an apprentice had a premature contract termination during the training period (=0) or not (=1). *own solutions* and *varied work* are significant again. Panels (C) and (D) further split PCTs by drop-out direction (Krötz and Deutscher, 2021): In panel (C), we look at "bad" PCTs, where apprentices left the education system or changed to less demanding occupations. For these bad PCTs, the same two training processes plus *autonomous work* and the FPC are significant. However, in panel (D), we look at "good" PCTs, where apprentices changed to more demanding occupations or a school-based education. There are no significant effects in this case. These results are consistent with a causal interpretation that good training processes improve education outcomes by reducing both bad PCTs and exam failure, but not PCTs that are favorable for the apprentices.

The effects of training processes might also differ by apprentice groups. Indeed, sample splits show that the effects are larger for male apprentices than for female apprentices, and for apprentices born in Switzerland than for apprentices not born in Switzerland (see Appendix Figure A8). An exception is the training process item *own solutions*, which has a particularly strong effect for those not born in Switzerland.

Finally, it is interesting to see how the results vary by occupation. Graduation is highest in the *healthcare, education, and social* sector, and lowest in the *food, catering, and household* sector (see Appendix Table A4). When we interact the training item *varied work* with the five occupation groups and test for the total effect of *varied work* in each occupational field, we see that there is no effect in the *healthcare, education, and social* sector, because graduation is practically universal there. In contrast, *varied work* has a substantial effect in the four other sectors, with the highest point estimates for *industry, technology, and information science* and secondly for *food, catering and household*, which both also include classical crafts occupations. Only the former effect is statistically significant, however, due to the reduced sample sizes per occupational field.

5.5 Assortative matching as an alternative explanation?

Positive assortative matching between good apprentices and firms would show in a positive correlation of training processes and education success. This would also weaken or even undermine the explanation that better training leads to better outcomes causally. We use additional variables to capture the matching between apprentices and firms. Model 3 in Table 3 includes such controls and shows that firms using assessment tests in recruiting and employing apprentices with higher mean grades in lower-secondary school[16] also have apprentices with higher education

[16] This variable is collected in the firm survey and is therefore available as a firm mean only, see section 4.3.

success. The negative effect of the log number of applications for apprenticeship places is the only counter-intuitive result.

The *matching controls* further include firm means of ability-related individual variables stemming from a larger sample of apprentices in the same firms based on the Altonji and Mansfield approach (see section 4.3). Indeed, the firm share of apprentices who attended the advanced track in lower-secondary school is positively related with exam success, even when controlling for individuals' track. This indicates that some assortative matching between firms and apprentices likely takes place. However, the other firm means are not significant, such that the scope of assortative matching seems limited.

We can also look directly at the correlations between matching controls and the training process items. These correlations (in Appendix Figure A9) are all positive, but small with a maximum of .16 between the share of female apprentices in a firm and planning training in advance. This correlation is likely explained by the higher share of female apprentices in the health sector, where the planning of training and other processes is prevalent. These weak correlations make it unlikely that there is strong assortative matching in hard-to-observe variables, as already argued in section 3.1. Firms with better training processes have only slightly better apprentices, and controlling for observable matching suggests that this is not the main driver of the association between training processes and education success.

5.6 Robustness analyses

In this subsection, we vary the specifications of our main estimations and perform a formal sensitivity analysis to discuss the potential of bias due to unobserved confounders. Our results in Figure 2 used the training processes in their original seven-point scale. If we put the rare first four values (1-4) together, or drop the rare firms stating a value below 4, the results remain almost unaffected. Furthermore, we checked for nonlinear effects by treating the original scale as categorical to investigate if there is any non-linearity in the effects. For example, there could be too much autonomy or varied work, resulting in an inverted U-shape of the effects. However, the results with dummy variables for each scale value show that the effects are uniformly increasing (all results available on request).

In firms with just one apprentice, the answers to the training process questions might be influenced by the ability of this apprentice. This happens if firms adapt training processes to the ability of their apprentice, which would also lead to an association between training processes and education success. E.g., a better apprentice may be allowed to work more autonomously. This problem is partly addressed by controlling for individual characteristics. A further possibility to counter this problem is to rely on a sample with as many apprentices per firm as possible. In model 4 in Table 3, we use all apprentices available in the register data for the firms in the CBS survey, including apprentices trained there before and after the survey time. Using this sample assumes that match quality and training processes are relatively stable over time. In this extended sample with more than 20,000 apprentices, we find similar results as in the main sample. We can also exclude firms with only one apprentice. Model 5 uses a sample where firms with less than three apprentices are excluded, such that processes in these firms cannot be tailored to single apprentices.[17] We again find a positive and significant coefficient for the training process *varied work*. Finally, if firms adapt their processes to apprentices, the association between training processes and graduation should be stronger in firms where apprentices have a similar performance level. If apprentices are diverse, it is difficult to adapt training processes. We do not find differences between firms that report large differences in the work performance between their apprentices and firms that see little difference (Appendix Figure A11).

We have argued that our control variables capture the main aspects that might lead to a spurious correlation between training processes and graduation. Yet, we cannot exclude for sure that there are confounders biasing the results. Examples of such confounders are unobserved firm characteristics, such as the overall efficiency of management, or measures that allow firms to learn more about apprenticeship candidates' ability than we observe in the data. Therefore, we now examine how important potential omitted variables needed to be to reverse the main findings in a formal sensitivity analysis (Altonji et al., 2005; Oster, 2019; Cinelli and Hazlett, 2020). We follow Cinelli and Hazlett (2020) (CH hereafter) and use contour plots

[17] Model 5 also alleviates concerns about measurement error in the firm means variables, because it also drops firms with a smaller number of observations to calculate the firm means. Figure A10 in the Appendix shows the distribution of apprentices per firm used to calculate these means.

to show how strong hypothetical one or several confounders would need to be to drive the positive coefficients on training processes in the main models to zero.

This CH approach requires a linear model. We create an outcome variable similar to the running example in Cinelli and Hazlett (2020) and in Hazlett (2020).[18] To do so, we collapse the main sample at the firm level, resulting in a graduation success rate per firm as the dependent variable. Figure A12 in the Appendix shows the distribution of this variable. Using this sample and the firm means of all formerly individual variables, including training process variables, we estimate OLS regression models. As Table A5 in the Appendix shows, the coefficient for *varied work* is very similar in the firm-level model as in the apprentice-level model. We use this coefficient for the sensitivity analysis.

The compelling use of the CH sensitivity analysis relies on finding "strong" observed covariates, i.e. one or more variables that are related to both the training process and graduation, which can be used as benchmark for unobserved influences. We choose two such variables from the model. The first variable is *assessment test*, which indicates whether firms use such tests when recruiting apprentices. It is correlated with *varied work* (Table 2) and with education success (Table 3). The same is true for the second variable, *grades* in lower secondary school. Together, these variables capture important aspects of apprentice ability and the matching between apprentices and firms.

Figure 4

The contour plot in Figure 4 uses these two variables as benchmark and *varied work* as the treatment variable. The basic idea of the contour plot is to position the effect of unobserved confounders (relative to the benchmark) in a coordinate system with the two partial correlations that determine omitted variable bias as axes: the horizontal axis measures how strong confounders are correlated with *varied work*, i.e. the variable of interest or treatment; the vertical axis measures their correlation with successful graduation, i.e. the outcome. These correlations are expressed as partial R-squared values. Figure 4 shows that an omitted variable or a set of

[18] Both use an outcome variable that captures individual attitudes towards peace. This variable ranges between 0 and 1, with high frequency at the endpoints of the range.

omitted variables needs to be more than seven times "as strong as assessment test and grades" to completely reverse the positive relationship between *varied work* and successful graduation found in Column 5 in Table A5. We conclude that with the set of control variables included in the regression models, which include ability proxies and the information that firms likely observe about apprenticeship candidates, it is unlikely that a set of omitted variables is strong enough to reverse the positive effects we reported for training processes on graduation.

6 Discussion and conclusions

In this paper, we use measures of the quality of training processes in firms to show that apprentices are more successful in graduating when they train in firms with good processes. This finding is important for two reasons: First, the literature about the role of firms in apprentice outcomes is still very scarce. Secondly, there is a substantial proportion of apprentices who interrupt or drop out of training, or fail at the final exam, leaving them at risk of entering the labor market without an upper-secondary degree. For all VET stakeholders, it is thus important to learn about factors fostering educational success.

In the estimations, two training processes stand out. Apprentices are significantly more successful in firms that make them find own solutions and in firms that assign more varied tasks. Both variables increase education success by 10 percent in separate models, and by 15 percent in total in a model containing all training process variables. These effects are driven by a reduction in final exam failure, on the one hand, and a reduction of downward dropouts to less challenging training occupations or longer training interruptions, on the other. The conditions for training in firms, such as time resources for firm trainers, are positively correlated with better training processes, but the effect of training processes on graduation remains unaffected by controlling for training conditions.

The positive association between training processes and education success could be caused by assortative matching between good apprentices and firms. However, it is unlikely that apprentices or firms can fully assess their respective quality because apprenticeship candidates do not yet have any labor market experience or history.

We control for apprentice and firm characteristics, which may be observable to both sides. We also use firm averages of apprentice characteristics in an extended sample, applying an approach favored by Altonji and Mansfield (2018) to control for sorting. None of these groups of variables are able to explain the association between training processes and education success. This speaks for a limited role of assortative matching in this particular setting.

To assess the potential effect of omitted variables more generally, we show that to reverse the positive effects presented in the paper, a set of unobserved confounders would have to be seven times stronger than the combined effect of firms using assessment tests in recruiting and apprentices' mean grades, both highly correlated with graduation. As we control for many variables that are related to training processes and graduation, such strong effects of unobservable variables are unlikely.

We conclude that increasing the quality of training processes may be a promising way to increase the proportion of apprentices graduating successfully on time. However, because increasing training quality may be costly, it is unclear what the optimal training quality is from the firms' and the society's point of view. Therefore, we end with a back-of-the-enveloppe estimation of firms' costs for increasing training quality. The CBS survey allows to calculate the gross cost of training for firms as well as the productive contribution emanating from apprentices' work (Gehret et al., 2019). The difference between apprentices' contribution and the gross cost of training is the net benefits. Regressing net benefits on *varied work* and controls in Appendix Table A6 shows that the benefits shrink, i.e. training becomes more costly, which is mainly due to increasing gross costs (lower panel of the table). According to the estimate in the last column of the table, an increase in *varied work* by one standard deviation leads to an increase in net training costs of ca. 500 CHF. This is not a huge effect, considering that the average net benefit of training for a Swiss firm is at roughly 2,000 CHF per year and apprenticeship.

Our results indicate that training firms and in particular their training quality matter for apprentices' education success. Promising next steps for research are to confirm the effect of training processes in firms in different contexts and different research designs, and to directly analyze the effect of policies or measures designed to improve training processes in firms.

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Table 1: Summary statistics

	N	Mean	Std. Dev.	Min.	Max.
Outcomes					
1(Graduation)	9538	0.78	0.41	0.00	1.00
1(Premature contract termination PCT)	9538	0.17	0.38	0.00	1.00
1(Failed exam)	9538	0.05	0.21	0.00	1.00
Training processes					
Agree on learning objectives	9538	5.92	1.25	1.00	7.00
Plan training in advance	9538	5.50	1.44	1.00	7.00
Autonomous work	9538	5.79	1.16	1.00	7.00
Own solutions	9538	5.75	1.17	1.00	7.00
Varied work	9538	5.74	1.05	1.00	7.00
Feedback	9538	5.82	1.14	1.00	7.00
Insight into production process	9538	5.92	1.18	1.00	7.00
Basic varaibles					
1(2013 apprentice contract)	9538	0.08	0.28	0.00	1.00
1(2014 apprentice contract)	9538	0.27	0.45	0.00	1.00
1(2015 apprentice contract)	9538	0.32	0.47	0.00	1.00
1(2016 apprentice contract)	9538	0.32	0.47	0.00	1.00
Apprentice characteristics					
1(Female)	9538	0.45	0.50	0.00	1.00
1(Born in Switzerland)	9538	0.88	0.32	0.00	1.00
1(Starting age 14-15)	9538	0.14	0.35	0.00	1.00
1(Starting age 16)	9538	0.46	0.50	0.00	1.00
1(Starting age 17)	9538	0.22	0.41	0.00	1.00
1(Starting age 18)	9538	0.07	0.26	0.00	1.00
1(Starting age 19-22)	9538	0.05	0.23	0.00	1.00
1(Starting age 23-25)	9538	0.02	0.15	0.00	1.00
1(Starting age 25+)	9538	0.03	0.18	0.00	1.00
1(Vocational baccalaureate)	9538	0.09	0.28	0.00	1.00
1(Trans. course lower-upper sec.)	9538	0.16	0.36	0.00	1.00
1(Advanced track compulsory school)	9538	0.56	0.50	0.00	1.00
Firm characteristics					
1(Industry)	9538	0.13	0.34	0.00	1.00
1(Construction)	9538	0.16	0.37	0.00	1.00
1(Service)	9538	0.43	0.50	0.00	1.00
1(Public or non-profit)	9538	0.28	0.45	0.00	1.00
1(Firm size 1-10)	9538	0.25	0.43	0.00	1.00
1(Firm size 10-49)	9538	0.36	0.48	0.00	1.00
1(Firm size 50-99)	9538	0.17	0.37	0.00	1.00
1(Firm size 99+)	9538	0.23	0.42	0.00	1.00
1(Personnel problem)	9538	0.47	0.50	0.00	1.00
1(Innovation ability)	9538	0.75	0.43	0.00	1.00
1(Efficiency)	9538	0.71	0.45	0.00	1.00
Salary apprentice	9538	1.06	0.25	0.19	3.99
Salary skilled worker	9538	5.39	1.00	3.00	12.00
Matching apprentice with firm					
ln(Number of applicants)	9538	2.26	1.06	0.00	5.86
1(Assessment test)	9538	0.64	0.48	0.00	1.00
1(First apprenticeship contract)	9538	0.92	0.27	0.00	1.00
Grades compulsory school (mean)	9538	0.00	1.00	-5.21	4.47
Female (mean)	9538	0.45	0.38	0.00	1.00
Born in Switzerland (mean)	9538	0.87	0.16	0.00	1.00
Starting age (mean)	9538	17.27	2.14	14.00	45.00
Vocational baccalaureate (mean)	9538	0.06	0.14	0.00	1.00
Trans. course lower-upper sec. (mean)	9538	0.14	0.17	0.00	1.00
Advanced track compulsory school (mean)	9538	0.54	0.34	0.00	1.00

Notes: Due to space restrictions, the basic variable *occupation* is not shown in the table, which includes 40 different occupations. All variable definitions, including the occupations, are available in Table A1.

Table 2: Relationships between training processes and firm variables, including firm means of apprentice characteristics

	Agree	Planning	Autonomy	Own solutions	Varied	Feedback	Insight	PC1
1(Construction)	-0.16	0.080	-0.16	-0.12	0.017	-0.15	0.21	-0.057
	(0.17)	(0.17)	(0.15)	(0.21)	(0.16)	(0.18)	(0.17)	(0.13)
1(Service)	-0.058	0.15	-0.25**	-0.012	-0.16*	-0.14	-0.16	-0.11
	(0.13)	(0.14)	(0.11)	(0.11)	(0.094)	(0.12)	(0.15)	(0.091)
1(Public or non-profit)	0.055	0.30**	-0.24**	-0.030	-0.013	0.0079	-0.12	-0.019
	(0.13)	(0.14)	(0.11)	(0.11)	(0.090)	(0.11)	(0.14)	(0.089)
1(Firm size 10-49)	0.073	0.35***	-0.097	-0.016	-0.14**	-0.064	-0.18***	-0.025
	(0.076)	(0.069)	(0.062)	(0.060)	(0.059)	(0.073)	(0.065)	(0.054)
1(Firm size 50-99)	0.027	0.41***	-0.21**	-0.12	-0.19**	-0.096	-0.56***	-0.13*
	(0.10)	(0.10)	(0.087)	(0.090)	(0.081)	(0.098)	(0.10)	(0.076)
1(Firm size 99+)	0.14	0.63***	-0.13	0.070	-0.082	0.086	-0.40***	0.036
	(0.13)	(0.11)	(0.092)	(0.086)	(0.088)	(0.11)	(0.10)	(0.081)
1(Personnel problem)	-0.090	-0.0062	-0.11**	0.015	-0.053	-0.19***	-0.12*	-0.094**
	(0.067)	(0.060)	(0.052)	(0.052)	(0.048)	(0.059)	(0.062)	(0.045)
1(Efficiency)	0.22***	0.31***	0.19***	0.27***	0.21***	0.23***	0.15**	0.26***
	(0.070)	(0.066)	(0.065)	(0.063)	(0.067)	(0.073)	(0.063)	(0.054)
1(Innovation ability)	0.20***	0.18***	0.15**	0.097	0.19***	0.20**	0.24***	0.20***
	(0.073)	(0.066)	(0.064)	(0.065)	(0.064)	(0.085)	(0.079)	(0.053)
ln(Number of applicants)	0.013	0.099***	0.022	-0.029	0.015	0.045	-0.011	0.023
	(0.032)	(0.033)	(0.029)	(0.027)	(0.027)	(0.031)	(0.033)	(0.025)
1(Assessment test)	0.26***	0.31***	0.12**	0.19***	0.15***	0.15***	0.12**	0.21***
	(0.060)	(0.058)	(0.055)	(0.054)	(0.051)	(0.058)	(0.054)	(0.045)
First apprenticeship contract (mean)	0.083	-0.0058	-0.0026	-0.070	0.12	-0.044	0.077	0.025
	(0.18)	(0.12)	(0.100)	(0.10)	(0.11)	(0.13)	(0.14)	(0.098)
Grades compulsory school (mean)	0.070**	0.082***	0.038	0.047*	0.055**	0.021	0.045	0.056**
	(0.030)	(0.031)	(0.026)	(0.025)	(0.025)	(0.027)	(0.031)	(0.023)
Female (mean)	0.012	0.095	0.047	0.10	0.062	0.27**	0.23*	0.13
	(0.14)	(0.14)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.098)
Born in Switzerland (mean)	0.42**	0.35*	0.16	0.23*	0.034	0.22	0.29*	0.26**
	(0.17)	(0.18)	(0.15)	(0.14)	(0.13)	(0.16)	(0.16)	(0.13)
Vocational baccalaureate (mean)	-0.094	-0.072	-0.20	-0.030	0.045	0.021	0.098	-0.039
	(0.20)	(0.20)	(0.18)	(0.18)	(0.16)	(0.19)	(0.23)	(0.15)
Trans. course lower-upper sec. (mean)	0.12	0.016	-0.14	0.095	-0.072	-0.13	-0.034	-0.030
	(0.15)	(0.15)	(0.13)	(0.13)	(0.12)	(0.17)	(0.13)	(0.12)
Advanced track compulsory school (mean)	-0.028	0.18	0.18*	0.17*	0.14	0.053	0.041	0.12
	(0.12)	(0.11)	(0.10)	(0.10)	(0.093)	(0.11)	(0.096)	(0.088)
R-squared	0.11	0.24	0.10	0.13	0.095	0.16	0.094	0.17
N	3792	3792	3792	3792	3792	3792	3792	3792

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are: Agree = agree on learning objectives, Planning = plan training in advance, Autonomy = autonomous work, Varied = varied work, Insight = insight into production process, and PC1 = first principal component. OLS regression with survey weights. The reference groups are manufacturing and firms with fewer than 10 employees. Not displayed in the table are 40 occupations, seven regions, the firm average of the entry year of the apprenticeship contract, the starting age of apprentices, and the salaries of both skilled workers and apprentices.

Table 3: Relationships between graduation, varied work and control variables

	(1)	(2)	(3)	(4)	(5)
Varied work	0.021***	0.021***	0.019***	0.017***	0.017***
	(0.0068)	(0.0061)	(0.0059)	(0.0052)	(0.0052)
1(Female)		0.022	0.025	0.039***	0.052***
		(0.019)	(0.021)	(0.013)	(0.012)
1(Born in Switzerland)		0.060**	0.048*	0.053***	0.052***
		(0.028)	(0.028)	(0.019)	(0.018)
1(Vocational baccalaureate)		0.096***	0.075***	0.092***	0.088***
		(0.018)	(0.023)	(0.016)	(0.016)
1(Trans. course low-upper sec.)		-0.035*	-0.044**	-0.056***	-0.041**
		(0.020)	(0.020)	(0.017)	(0.017)
1(Advanced track compulsory school)		0.12***	0.089***	0.054***	0.055***
		(0.017)	(0.018)	(0.011)	(0.012)
1(Firm size 10-49)		0.025	0.024	0.017	0.016
		(0.016)	(0.016)	(0.014)	(0.012)
1(Firm size 50-99)		0.051**	0.059***	0.039**	0.023
		(0.021)	(0.021)	(0.016)	(0.016)
1(Firm size 99+)		0.056***	0.059***	0.064***	0.052***
		(0.022)	(0.021)	(0.017)	(0.017)
1(Personnel problem)		-0.0015	-0.0044	-0.0044	-0.016
		(0.013)	(0.012)	(0.010)	(0.0097)
1(Innovation ability)		-0.027	-0.027*	-0.015	-0.0049
		(0.016)	(0.015)	(0.014)	(0.011)
1(Efficiency)		0.031**	0.029**	0.013	-0.0015
		(0.015)	(0.014)	(0.013)	(0.011)
Salary apprentice		0.032	0.026	-0.0082	0.012
		(0.031)	(0.030)	(0.021)	(0.020)
Salary skilled worker		0.015**	0.014**	0.015***	0.016***
		(0.0071)	(0.0068)	(0.0051)	(0.0052)
1(First apprenticeship contract)			0.038	0.039**	0.038*
			(0.028)	(0.020)	(0.021)
ln(Number of applicants)			-0.026***	-0.020***	-0.011**
			(0.0070)	(0.0052)	(0.0048)
1(Assessment test)			0.039***	0.026**	0.011
			(0.013)	(0.010)	(0.0097)
Grades compulsory school (mean)			0.025***	0.025***	0.023***
			(0.0069)	(0.0049)	(0.0050)
Female (mean)			-0.020	-0.0067	0.0044
			(0.040)	(0.032)	(0.034)
Born in Switzerland (mean)			0.044	0.059	0.14***
			(0.049)	(0.039)	(0.047)
Vocational baccalaureate (mean)			0.049	0.036	0.041
			(0.053)	(0.042)	(0.042)
Trans. course lower-upper sec. (mean)			0.032	0.080	0.017
			(0.047)	(0.049)	(0.049)
Advanced track compulsory school (mean)			0.090***	0.13***	0.14***
			(0.028)	(0.024)	(0.027)
R-squared	0.044	0.093	0.10	0.10	0.11
N	9538	9538	9538	20583	18479

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regressions with standard errors clustered by firm are reported in parentheses. The results are weighted using sampling weights. All columns include fixed effects for occupation and the apprentice's starting contract year. Column 2 also includes four sector dummies and seven region dummies (not shown in the table). The reference group is firms with fewer than 10 employees. Column 4 includes an extended sample that incorporates apprentices from additional cohorts. Column 5 represents the extended sample but excludes firms with fewer than 3 apprentices from this extended sample.

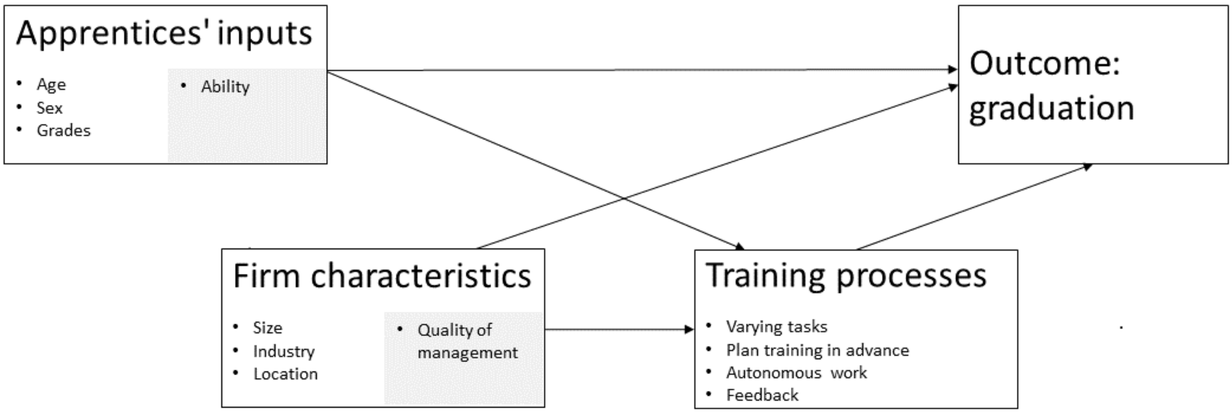
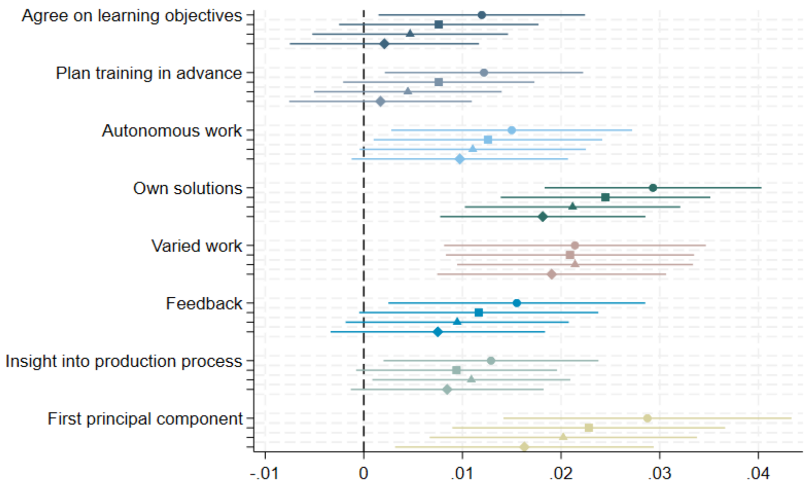


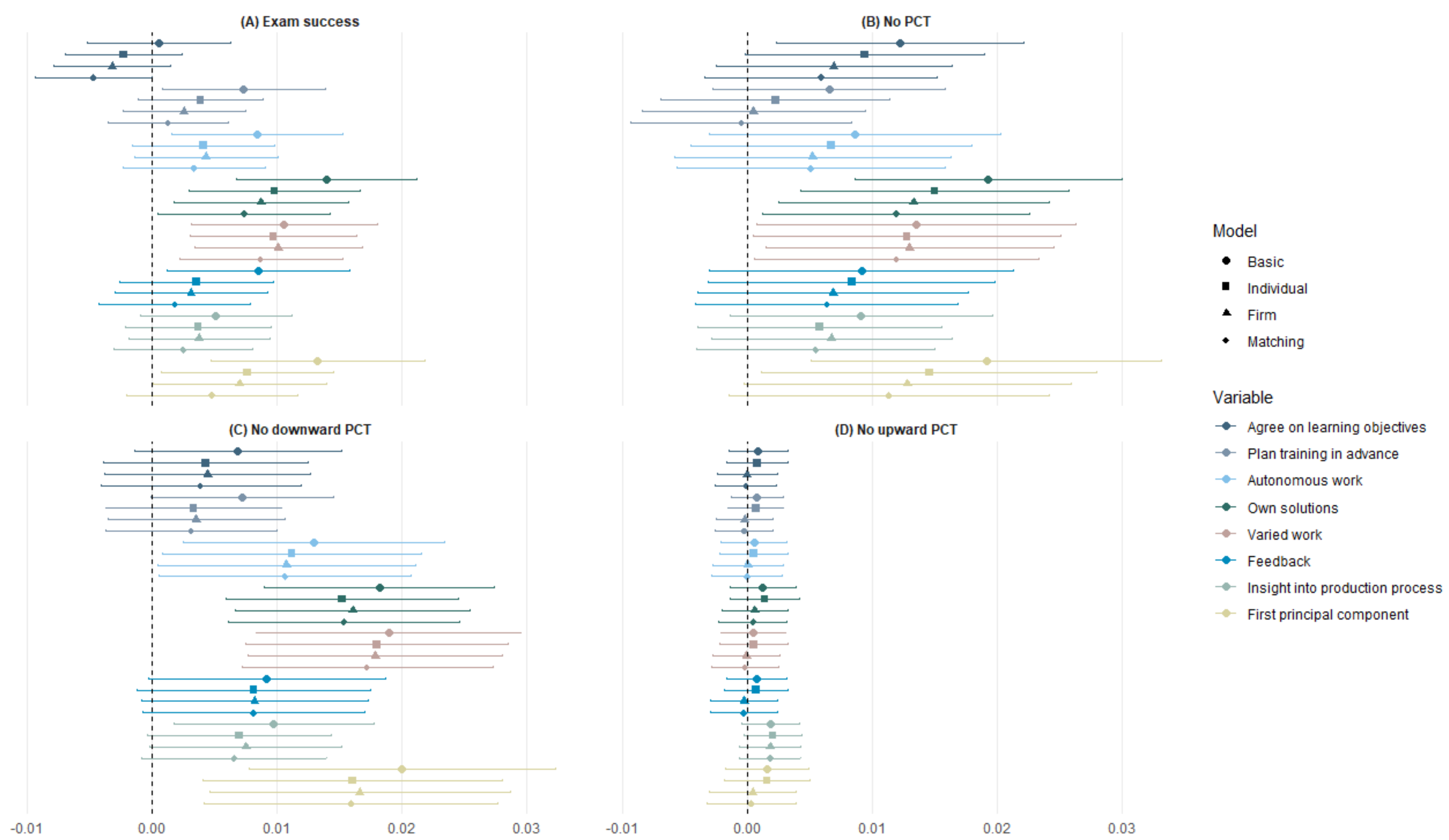
Figure 1: Model of firm training and graduation

Figure 2: Graduation and training processes



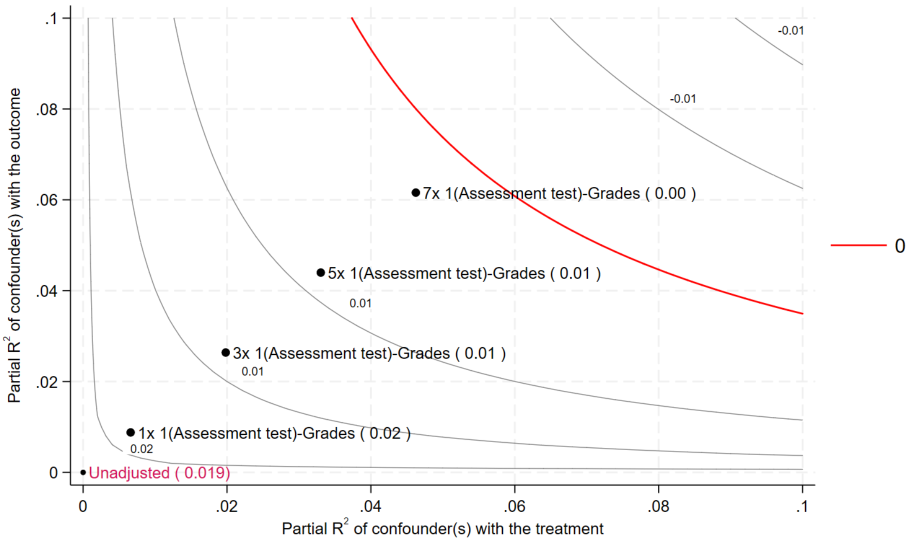
Notes: This figure illustrates the association between graduation and various training processes. All coefficients are derived from separate OLS regression models, each with 95% confidence intervals. The results are weighted using sampling weights. The last four models incorporate a first principal component derived from all training processes, rather than focusing on a single training process. Basic variables (represented by circles) include occupation and the apprentice's initial contract year. Individual characteristics (depicted by squares) encompass gender, immigration status, apprenticeship starting age, participation in a vocational baccalaureate during the apprenticeship, apprentices from advanced tracks in compulsory school, and enrollment in a transitional course between lower and upper secondary school. Characteristics of a firm, (represented by triangles) includes the sector, firm size, broader regional locations, firm performance metrics such as innovation capacity, efficiency, and personnel challenges, along with wages for apprentices and skilled workers. A comprehensive set of controls (shown as diamonds), also contains matching apprentices and firm variables: indicators for first-time apprentices and assessment tests, the number of applicants, as well as firm averages of grades, apprentices from advanced tracks, gender, immigration, starting age, vocational baccalaureate, and transition course. The number of observations is 9,538. The full regression table for the training process *varied work* is presented in Table 3.

Figure 3: Final exam vs No PCT and No downward PCT vs No upward PCT



All coefficients are from different OLS regression models, with 95% confidence intervals. Results are weighted with sampling weights. The variables included are depicted by the different symbols. In Panel A, apprentices with a PCT are excluded i.e. the outcome variable is passing the final exam. In Panel B,C, and D the outcome variable is coded as 1 if the apprentice did not have a PCT and 0 if they did. In Panel C, the sample is reduced by apprentices who dropped out for equal or more advanced occupations and higher education. In panel D, the sample is reduced by apprentices who dropped out for equal or less advanced occupations and of the education system.

Figure 4: Sensitivity contour plots for varied work with two benchmarks



Notes: The reference variables are an assessment test and grades, showing hypothetical confounders once, three, five, or seven times as strong as the combination of the two variables. The horizontal axis shows hypothetical values for the percentage of the residual variance of the treatment explained by the confounders. The vertical axis shows hypothetical values for the percentage of the residual variance of the outcome explained by the confounders. The red line represents the zero effect.

Appendix: Additional Tables and Figures

see Tables A1, A2, A3, A4, A5, and A6 and Figures A5, A6, A7, A8, A9, A10, A11, and A12

Table A1: Variable definitions and sources

Variable	Definition	Source
Outcome variable		
Graduation	Assigned 1 if the apprentice did not experience any contract termination and successfully passed the final exam on the first attempt.	LABB
Training processes		
Training processes	Evaluated based on a trainer's ratings of specific training-related statements on a 1 (does not apply at all) to 7 (fully applies) scale. These seven items, translated from German, include: 'I set learning objectives with the apprentices', 'I plan training units in advance', 'I assign tasks that enable autonomous work/practice', 'I let apprentices find their own solutions', 'I ensure apprentices are given varied tasks', 'I regularly provide apprentices feedback on their work', 'Apprentices gain insights into all production process phases'. A composite measure is derived using the first principal component of these items and is standardized to a standard deviation of one.	CBS
Basic variables		
Occupations	The estimations include apprentices from the 40 largest training occupations (5 aggregated occupations), for which we include a dummy each: assembly electrician (2), assistant in hospitality services (1), automotive mechatronics technician (3), automation technician (3), automotive painting technician (3), automotive technician (3), baker (1), bricklayer (2), building and grounds custodian (2), building services technician (2), cabinet-maker (2), carpenter (2), cook (1), commercial employee- basic education (4), commercial employee- extended education (4), dental assistant (5), draftsman (2), druggist (4), electrician (2), gardener (2), geomatics draftsman (2), hairdresser (1), health and social care assistant (5), healthcare worker (5), hotel specialist (1), information technologist (3), logistics specialist (4), machine design draftsman (3), medical assistant (5), metal worker (3), optician (5), painter (2), pharmacy assistant (4), plumber (2), polymechanic technician (3), professional in hospitality services (1), restaurant specialist (1), retail assistant (4), retail professional (4), and social care worker (5).	CBS

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Table A1: Variable definitions and sources (continued)

Variable	Definition	Source
Aggregated occupations	The five aggregated occupations are classified based on the Swissdoc codes for occupations[19]. The five aggregated occupations are: 1) food, catering, and household, 2) construction, 3) industry, technology, and information science, 4) economy, trade, administration, transport, and tourism, and 5) health, education, sport, social affairs, theology, and psychology. The specific occupations belonging to each of these aggregated groups are listed above in the table in parentheses.	CBS
Apprenticeship contract	Categorized according to the year of entry into the current apprenticeship contract, resulting in four distinct categories spanning from 2013 to 2016 (for the main sample).	LABB
Apprentice characteristics		
Female	Assigned 1 for females and 0 for males.	LABB
Born in Switzerland	Assigned 1 for individuals born in Switzerland.	LABB
Starting age	Derived from the birth year and the initial apprenticeship start date, segmented into 7 distinct age groups.	LABB
Vocational baccalaureate	Assigned 1 for apprentices aspiring to attain a vocational baccalaureate during their training period.	LABB
Advanced track compulsory school	Assigned a value of 1 for apprentices in an advanced track in compulsory school, and 0 otherwise.	LABB
Transition course lower-upper sec.	Indicates if an apprentice attended a transition course after compulsory school (lower secondary), usually when an apprenticeship (upper secondary) is not secured on the first attempt (1 if yes, 0 if no).	LABB
Firm characteristics		
Sector	Categorized into 4 types: industry, construction, service, and public or non-profit	CBS
Firm size	Categorized into 4 different groups to reflect the size of the firm.	CBS
Regions	Categorized based on the firm's location within 7 broader geographic regions in Switzerland.	CBS
Personnel problem	Assigned a value of 1 if an employee at the firm indicated any of the following personnel problems (translated from German): 'Too many staff', 'Emigration of skilled workers', 'Insufficient qualifications/inadequate competency profile in the skilled worker sector', 'Lack of work motivation', or 'High levels of absence/high levels of sickness absence'. If no personnel problem was indicated, a value of 0 was assigned.	CBS

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[19] The classification codes used by career counselors are sourced from the following website: https://swissdoc.sdbb.ch/

Table A1: Variable definitions and sources (continued)

Variable	Definition	Source
Innovation ability	Evaluated based on employees' ratings of 'How do you rate the situation of your company with regard to its ability to innovate?' The evaluation uses a scale from 1 (very bad) to 5 (very good). The variable takes a value of 1 if the rating is either 4 (rather good) or 5 (very good); otherwise, it takes a value of 0.	CBS
Efficiency	Evaluated based on employees' ratings of 'How do you rate the situation of your company with regard to its efficiency of production/business processes?' The evaluation uses a scale from 1 (very bad) to 5 (very good). The variable takes a value of 1 if the rating is either 4 (rather good) or 5 (very good); otherwise, it takes a value of 0.	CBS
Salary apprentice*	Annual salary for apprentices, including a 13th-month salary, stated in thousands of francs, as evaluated by a company employee.	CBS
Salary skilled worker	Monthly salary for a skilled worker in this profession, in thousands of francs, as evaluated by a company employee.	CBS
Matching of apprentices and firms		
Number of applicants	Logarithm of the number of applicants for each apprenticeship position.	CBS
Assessment test	Indicates if a firm uses any assessment tests (either developed in-house or standardized) in the apprentice selection process (1 if yes, 0 if no).	CBS
First apprenticeship contract	The value is 1 if an apprentice had a previous apprenticeship contract (excluding apprentices who did not start in the first apprenticeship year); otherwise, the value is 0.	LABB
Grades compulsory school	Average compulsory school grades of apprentices in mathematics, first language, and second language, reported by the firm. A principal component analysis is used for this measure.	CBS
Firm averages of apprentice characteristics	The calculations of these firm averages are based on an larger sample of almost 36,000 apprentice contracts between 2011 and 2020. The apprentice characteristics include gender, immigration status, starting age, vocational baccalaureate, participation in a transition course between lower and upper secondary levels, and advanced track in compulsory school.	LABB
Further training variables		
Time resources trainer	Assessed by trainers rating their available time resources for training on a 1 to 7 scale. Very little time resources (1-3) are combined due to fewer observations.	CBS
Training plan	Categorized into 3 types: no training plan, a plan from a professional association, or an in-house developed plan (None of these plans refer to the official educational plan by SERI.).	CBS

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Table A1: Variable definitions and sources (continued)

Variable	**Definition**	**Source**
Share of skilled work in training	A trainer assesses the proportion of skilled work typically performed by skilled workers within the firm. Non-skilled work includes simpler activities or work that do not directly contribute to the company's productivity, such as participating in instructed tasks and engaging in self-study.	CBS

Notes: *A limitation of the CBS is that it reports salary for the current training year of an apprentice. For firms with only one apprentice in a three-year program, we only have data for one of the three years. To address data gaps, we use the available salary data alongside firm-specific variables (such as region, occupation, firm size, and sector) to impute missing values. We imputed missing values once using chained equations (linear regression) and different education lengths have been imputed separately.

Table A2: Graduation and training processes (one model)

	Basic	Individual	Firm	Matching
Agree on learning objectives	-0.00017	-0.0018	-0.0029	-0.0039
	(0.0069)	(0.0066)	(0.0061)	(0.0059)
Plan training in advance	0.0027	-0.00038	-0.0027	-0.0044
	(0.0063)	(0.0061)	(0.0058)	(0.0057)
Autonomous work	-0.0059	-0.0041	-0.0034	-0.0014
	(0.0072)	(0.0069)	(0.0070)	(0.0067)
Own solutions	0.026***	0.022***	0.018***	0.016**
	(0.0069)	(0.0068)	(0.0069)	(0.0066)
Varied work	0.0097	0.014*	0.017**	0.016**
	(0.0083)	(0.0077)	(0.0075)	(0.0074)
Feedback	-0.00069	-0.0025	-0.0040	-0.0035
	(0.0079)	(0.0075)	(0.0071)	(0.0069)
Insight into production process	0.0035	0.0011	0.0044	0.0029
	(0.0066)	(0.0063)	(0.0063)	(0.0061)
R-squared	0.048	0.084	0.095	0.11
Joint significance (p-value of F-test)	0.000045	0.00050	0.0014	0.0045
N	9538	9538	9538	9538
Basic controls	YES	YES	YES	YES
Apprentice controls	NO	YES	YES	YES
Firm controls	NO	NO	YES	YES
Matching and firm mean controls	NO	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: This table show associations between graduation and several training processes. The coefficients are from OLS regressions with standard errors clustered by firm in parentheses. All columns include controls for occupation and the year of the apprenticeship contract. In column 2, apprentice controls (gender, immigration status, apprenticeship starting age, participation in a vocational baccalaureate during the apprenticeship, enrollment in a transitional course between lower and upper secondary school, and completion of the advanced track in compulsory school) are added. Column 3 introduces firm controls (sector, firm size, broader regional locations, firm performance metrics such as innovation capacity, efficiency, and personnel challenges, along with wages for apprentices and skilled workers.) and in column 4, matching apprentices and firm mean variables (indicators for first-time apprentices and assessment tests, the number of applicants, as well as firm averages of grades, apprentices from advanced tracks, gender, immigration, starting age, vocational baccalaureate, and transition course.) are added.

Table A3: Relationships between training processes and further training variables

	Agree	Planning	Autonomy	Own solutions	Varied	Feedback	Insight	PC1
Time resources trainer	0.22***	0.20***	0.18***	0.16***	0.19***	0.23***	0.18***	0.22***
	(0.019)	(0.021)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.014)
1(Prof. association training plan)	0.38***	0.49***	0.15***	0.28***	0.14**	0.30***	0.16***	0.30***
	(0.066)	(0.060)	(0.052)	(0.052)	(0.053)	(0.055)	(0.053)	(0.042)
1(Own training plan)	0.52***	0.58***	0.25***	0.28***	0.18***	0.35***	0.17**	0.37***
	(0.076)	(0.076)	(0.066)	(0.071)	(0.061)	(0.077)	(0.079)	(0.054)
Share of skilled work in training	0.0023	0.0020	0.0067***	0.0023	0.0041***	0.0052***	0.0037**	0.0044***
	(0.0016)	(0.0016)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0011)
R-squared	0.18	0.30	0.16	0.17	0.16	0.24	0.14	0.28
N	3792	3792	3792	3792	3792	3792	3792	3792

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variables are: Agree = agree on learning objectives, Planning = plan training in advance, Autonomy = autonomous work, Varied = varied work, Insight = insight into production process, and PC1 = first principal component. OLS regression was conducted using survey weights. The regressions included the same variables as listed in Table 2, along with further training-related variables. The reference group in this analysis is the group with no training plan.

Table A4: Relationships between graduation, varied work and 5 occupation groups

	Basic	Individual	Firm	Matching
Varied work	0.026**	0.025***	0.025***	0.023**
	(0.010)	(0.0093)	(0.0091)	(0.0090)
1(Food)	-0.18	-0.12	-0.15	-0.11
	(0.15)	(0.14)	(0.14)	(0.14)
1(Industry)	0.036	0.012	-0.035	-0.034
	(0.15)	(0.14)	(0.13)	(0.13)
1(Economy)	0.15	0.16*	0.096	0.11
	(0.097)	(0.094)	(0.088)	(0.086)
1(Health)	0.36***	0.33***	0.33***	0.33***
	(0.087)	(0.086)	(0.091)	(0.090)
Varied work X 1(Food)	0.026	0.021	0.020	0.017
	(0.025)	(0.023)	(0.023)	(0.023)
Varied work X 1(Industry)	0.0044	0.0053	0.0052	0.0046
	(0.024)	(0.023)	(0.022)	(0.022)
Varied work X 1(Economy)	-0.0073	-0.013	-0.0091	-0.0076
	(0.017)	(0.015)	(0.014)	(0.014)
Varied work X 1(Health)	-0.042***	-0.033**	-0.040***	-0.035**
	(0.014)	(0.014)	(0.015)	(0.014)
R-squared	0.022	0.067	0.081	0.090
N	9538	9538	9538	9538

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regressions with standard errors clustered by firm in parentheses. Results are weighted with sampling weights. 40 occupations have been consolidated into five larger occupation groups. The baseline group is 'Construction'. The full definitions of the other groups are: 1) food, catering, household 2) industry, technology, information science 3) economy, trade, administration, transport, tourism 4) health, education, sport, social affairs, theology, psychology.

Table A5: Graduation and training processes with firm collapsed data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agree on learning objectives	0.00048							
	(0.0042)							
Plan training in advance		-0.0036						
		(0.0039)						
Autonomous work			0.0074					
			(0.0046)					
Own solutions				0.013***				
				(0.0046)				
Varied work					0.019***			
					(0.0051)			
Feedback						0.0098**		
						(0.0048)		
Insight into production process							0.0082*	
							(0.0045)	
First principal component								0.012**
								(0.0055)
R-squared	0.12	0.12	0.12	0.13	0.13	0.12	0.12	0.12
N	3792	3792	3792	3792	3792	3792	3792	3792

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the associations between graduation and various training processes. The coefficients are from OLS regressions with standard errors clustered by firm (in parentheses). The sample is aggregated at the firm level, with all variables representing firm averages. All columns include basic controls, apprentice controls, firm controls, as well as matching and firm mean controls.

Table A6: Cost and benefit and varied work

Panel A: Net benefit				
Varied work	-400.9*	-470.8**	-491.4**	-496.4**
	(207.5)	(204.6)	(200.2)	(201.2)
Panel B: Gross Cost				
Varied work	173.7	376.4**	422.4***	398.0***
	(157.7)	(151.6)	(143.6)	(144.2)
N	3792	3792	3792	3792
Basic controls	NO	YES	YES	YES
Firm controls	NO	NO	YES	YES
Matching and firm averages controls	NO	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the associations between net benefit (Panel A) or gross cost (Panel B) and varied work, including other control variables.

Figure A5: Histograms training processes

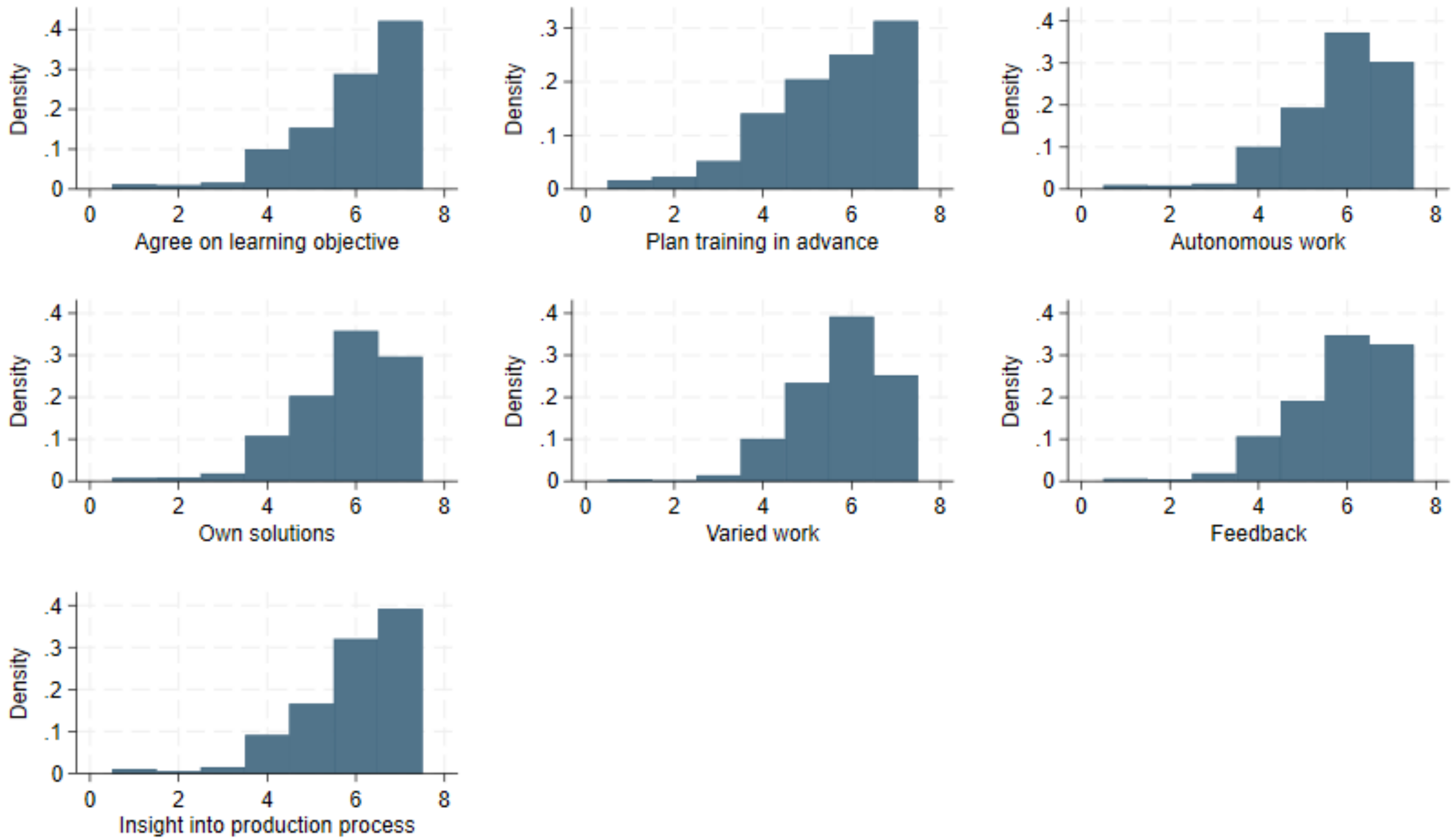


Figure A6: Correlations training processes

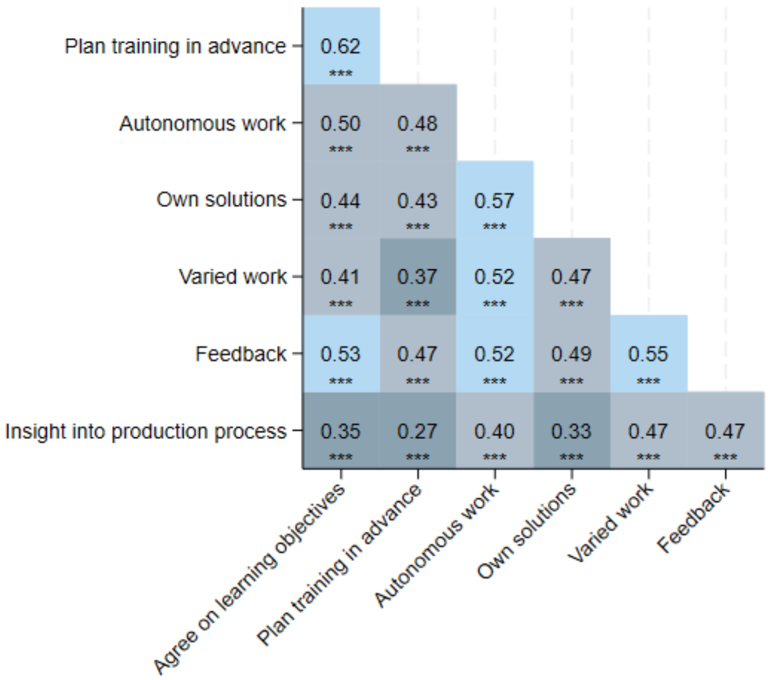
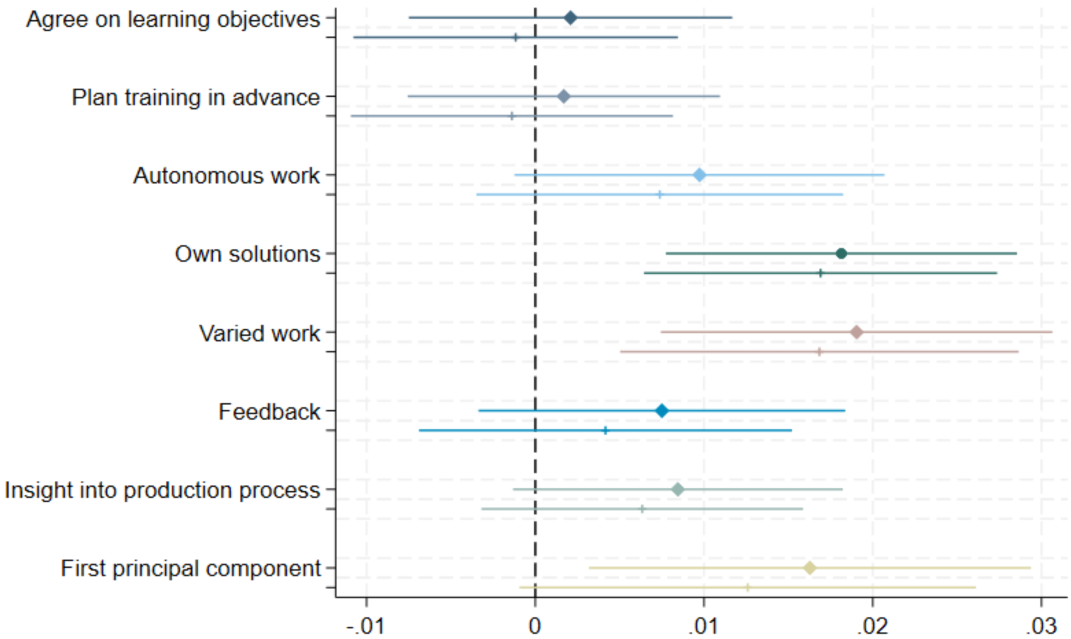
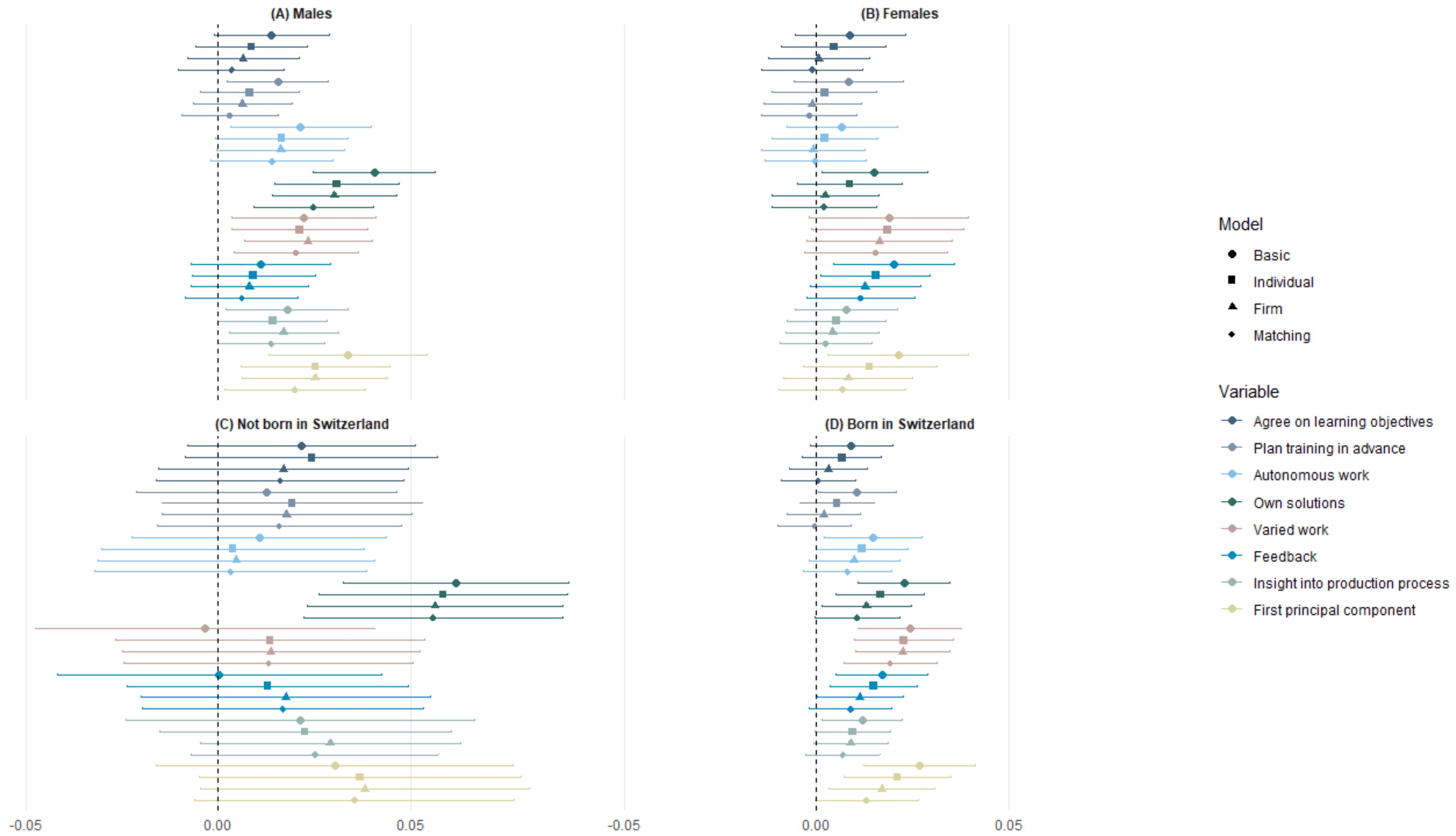


Figure A7: Graduation and training processes including further training variables



Notes: This figure illustrates the relationship between graduation and various training processes. The coefficients are derived from separate OLS regression models, each with 95% confidence intervals, and the results are weighted using sampling weights. The diamond-shaped point estimates correspond to those in Figure 2, meaning they account for basic controls, apprentice controls, firm controls, as well as matching and firm mean controls. Further training variables (denoted as x) are included in these regressions, such as training plans, time resources trainer, and the share of skilled work in training.

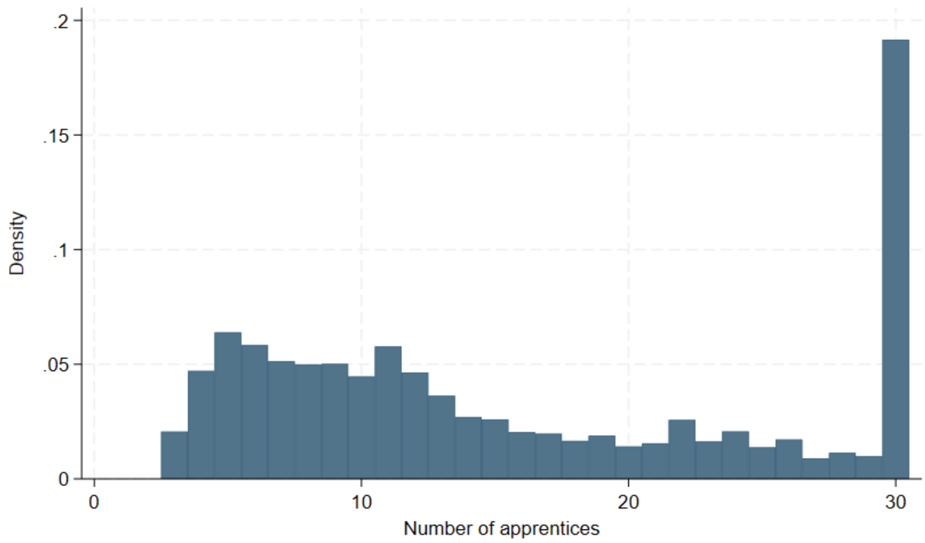
Figure A8: Split sample: gender and immigration status



Notes: This figure shows the association between graduation and different training processes. All coefficients are from different OLS regression models, with 95% confidence intervals. Results are weighted with sampling weights. In Panel A and B the sample is split by gender (The number of males is 5,239, and the number of females is 4,299.). In Panels C and D the sample is split by immigration status (The number of apprentices that were born outside of Switzerland is 1,130 and the number of apprentices born in Switzerland is 8,408.).

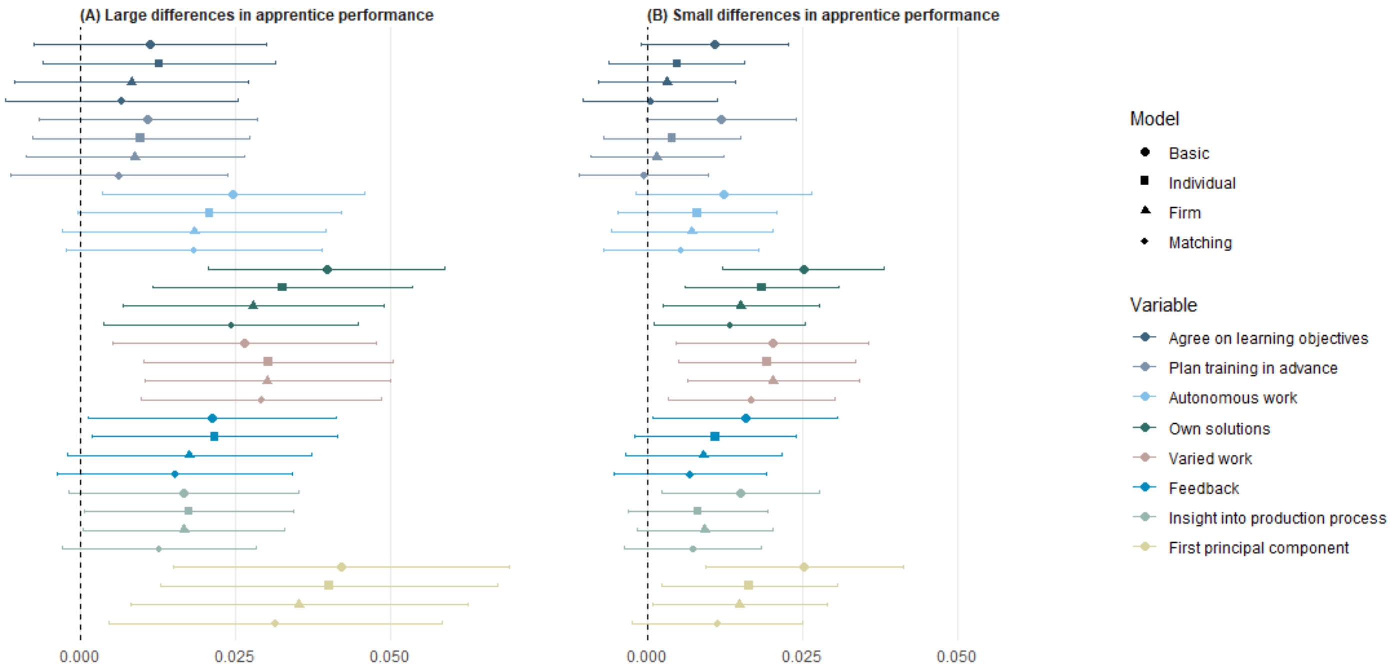
Figure A9: Correlations training processes and apprentice characteristics

Figure A10: Number of apprentices used to calculate firm means



This histogram illustrates the number of apprentices used to compute firm-level means for apprentice characteristics, with the exception of the advanced track due to fewer apprentices being included because of some missing data. The categories for 30 and 30+ have been merged. This sample corresponds exactly to Table 3, Model 5, where apprentices in small firms have been excluded.

Figure A11: Split sample: firm disparity in apprentice performance



Notes: This figure illustrates the relationship between graduation rates and various training processes, as determined by different OLS regression models with 95% confidence intervals. The results have been adjusted using sampling weights. The sample is divided based on the variation in apprentice performance within firms. Panel A presents results from firms where there is a large or very large disparity in performance among apprentices (N=3,565). Panel B, on the other hand, includes data from firms where apprentice performance differences are moderate, small, or nonexistent (N=5,678).

Figure A12: Firm's graduation rate