Does Human Capital Theory Govern the Relationship between Training Provision and the Business Cycle? Evidence from Switzerland

Guillaume M. Morlet, Thomas Bolli

Abstract

This paper evaluates the causal impact of business cycle fluctuations on the supply of dual vocational education and training positions. Human capital theory asserts training is procyclical; firms reduce training expenditure amidst economic downturns as future cash flows become increasingly uncertain, affecting labour demand dynamics. A conflicting strand of literature asserts that training provision is countercyclical. In recessions, the cost of labour inputs diminishes as labour markets become looser. Firms durably secure their future labour force at cheaper prices.

We execute multi-way fixed effects regressions applied to both Swiss survey and administrative data, using unemployment, and subsequently the Swiss KOF business situation indicator, as proxies for the business cycle. Unemployment is consistently negatively, however insignificantly, related to the supply of dual VET positions. On the other hand, the sign of the effect of the business situation indicator on the supply of dual VET positions varies, albeit in our sample, the business situation indicator does not significantly affect the supply of dual VET positions. We do not find evidence that the impact of the business cycle, as proxied by the aforementioned variables, on dual VET positions supply is significantly heterogenous between knowledge-intensive and non knowledge-intensive business services sectors. The impact of the business situation indicator on the supply of dual VET positions is significantly more negative on the construction sector than in the manufacturing sector, however this impact is not heterogeneous across other sectors.

Keywords: Business cycle; Labour demand; Training; Unemployment; Economic Sentiment; Multi-way Fixed Effects

JEL Classification: J23, J01, J69

1. Introduction

Dual vocational education and training[1] (VET) serves as a barrier against youth unemployment and shortages of skilled labour (Bolli et al., 2021). Nonetheless, this mode of knowledge transmission and training is susceptible of being adversely affected by economic downturns (see e.g. Brunello, 2009, Luethi and Wolter, 2020) such as the COVID pandemic (Muehlemann et al., 2020).

Over the second quarter of 2020, Switzerland's GDP fell by 8.2% following a slump in activity induced by the COVID19 pandemic, representing the biggest fall in GDP witnessed by the Helvetian nation since quarterly records began in 1980 (State Secretariat for Economic Affairs, SECO, 2020). In parallel, OECD (2022) data indicates that Switzerland's unemployment rate soared to 3.14% in 2020, a 37% increase on 2019 figures and the largest surge in unemployment since the great financial crisis (unemployment reached 3.7% in 2009). However, Goller and Wolter (2021) assert that both at the onset of the pandemic in April 2020 and over the second quarter of 2020, the supply of dual VET positions was hardly affected by the pandemic-related reduction in activity. This descriptive evidence suggests that in Switzerland, dual VET positions have evolved in an acyclical manner in recent years.

We posit that two counteracting forces drive the reaction of the number of dual VET positions, equivalently referred to as training provision in this paper, to the business cycle. These two forces may have cancelled each other out to yield the acyclicality of training highlighted by Goller and Wolter (2021) and Baldi et al. (2014): the income and substitution effects. Amidst economic downturns, a firm's financial situation tends to deteriorate and uncertainty increases, prompting firms to cut down on non-essential expenses to focus on mitigating financial distress. This entails reducing training expenses: it is the substitution effect[2]. On the other hand, during economic downturns, labour becomes periodically relatively cheaper, which might entice firms to increase training to durably secure its labour force at lower costs. This represents the income effect.

Two conflictual strands of literature oppose each other on this topic. Human capital theory (Becker, 1962) suggests that the substitution effect dominates the training – business cycle relationship. More recent scholars (e.g. Brunello and Bertoni, 2021) argue that in advanced economies, such as Switzerland, the income effect dominates the training – business cycle relationship. This topic has thus received much attention, in large part due to its high policy relevance. Understanding firms' training behaviour is essential for policymakers to best infer when training firms are in most need of support schemes (financial, regulatory, compliance, etc.) and employ taxpayer funds efficiently.

[1] UNESCO defines dual VET as a programme combining an apprenticeship component, through which apprentices frequent a workplace, and an instruction component, through which apprentices attend courses at a vocational school (see https://unevoc.unesco.org/home/Dual+System).

[2] Kimball and Shapiro (2008) assert that in this context, the substitution effect relates closely to the elasticity of newly offered dual VET positions to fluctuations in the business cycle.

We add to the literature on the relationship between training provision and the business cycle through the addition of sources of variation to our main regressor and dependent variable for more precise identification. Whilst two papers on this topic (Luethi and Wolter, 2020, Muehlemann et al., 2020) consider two sources of variation in their key explanatory variable used to proxy for the business cycle, namely geographical and temporal, our original contribution is to add a third source of variation to our proxy for the business cycle (unemployment): sectoral. The addition of sectoral variation to our regressor allows for a more precise identification of the causal effect of interest and allows the inclusion of a richer set of fixed effect vectors, controlling for more unobserved confounding factors. Our dependent variable also bears multiple sources of variation: respondent, occupation, canton, recruitment season (corresponding to the year) and month.

Our original contribution is thus to evaluate the causal impact of business cycle fluctuations on the provision of dual VET positions in Switzerland, gauging training provision in a unique way. Unemployment has been proven to be the most important macroeconomic factor in explaining training provision (Westergaard-Nielsen and Rasmussen, 2000). We thus first use unemployment, in our main analysis, as a proxy for the business cycle (see Okun, 1962, for a discussion of the relationship between unemployment and the business cycle), in line with Baldi et al. (2014), Brunello (2009) and Askilden and Nilsen (2005). Subsequently, for robustness and completeness, we replace unemployment by the Swiss KOF business situation indicator to quantify business cycle fluctuations[3], thereby replace administrative unemployment data by companies' sentiment regarding their current business situation collected through monthly surveys.

In all preferred specifications, unemployment is insignificantly associated with the supply of dual VET positions. We do not find a significant association between the KOF indicator and the supply of dual VET positions, aside from the construction sector, for which we find a significantly more negative effect of the business situation indicator on dual VET positions supply relative to the manufacturing sector. We do not find a significantly heterogenous relationship between business cycle proxies and the supply of dual VET positions across sectors. Finally, our findings do not highlight significant heterogeneity in the business cycle-dual VET positions provision relationship across knowledge-intensive and non knowledge-intensive sectors.

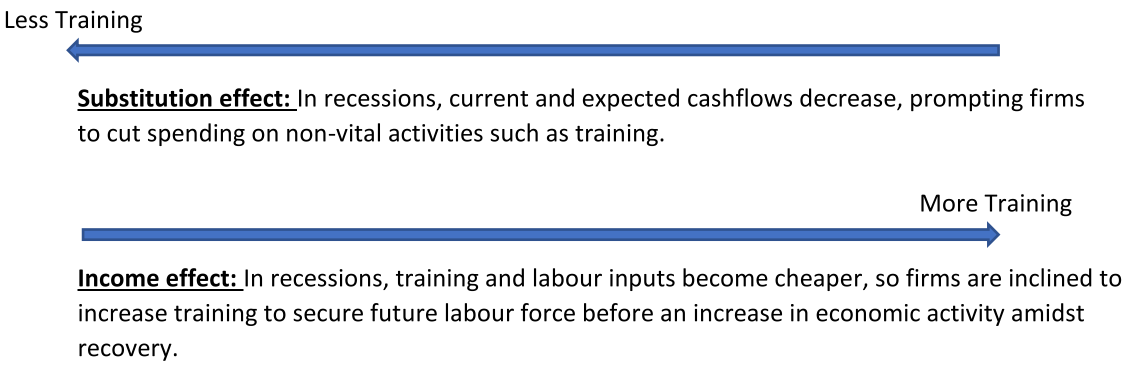
The remainder of the paper is structured as follows. Section 2 reviews literature investigating the relationship between training provision and then macroeconomic environment, whilst section 3 elicits the sources of the data we employ in our analysis, in addition to providing summary statistics. Section 4 expands on the econometric methods used to identify the causal effect of unemployment on training provision. Section 5 discusses our results and section 6 offers concluding remarks.

[3] See KOF (2022).

2. Literature Review

This section serves to place our paper in the context of the literature on the impact of business cycle fluctuations on the supply of dual VET positions. Additionally, this section contains a review of pertinent literature, culminating in the formulation of two alternative hypotheses tested in section 4. The literature is conflictual concerning the response of training provision to business cycle fluctuations (Brunello, 2009), as two forces – income and substitution effects - counteract each other:

Figure 1: Substitution and Income Effect – Training and Economic Downturns



Source: Author's Own Elaboration

2.1. The Procyclicality of Training Provision

Classical human capital theory, in support of the substitution effect's domination, stipulates that firms would not incur net losses to provide training to dual VET students (Becker, 1962). Firms training dual VET students may be faced with an economic downturn incurring a decline in present and expected future cashflows. In this configuration, human capital theory predicts that firms respond by reducing training provision, which is consequently countercyclical.

Luethi and Wolter (2020) and Muehlemann et al. (2020) argue that the supply of dual VET positions responds to the business cycle fluctuations in Switzerland and Germany respectively. Luethi and Wolter (2020) show that in Switzerland, the supply of dual VET positions is moderately pro-cyclical, and economic shocks are persistent over several years. This finding is corroborated by Muehlemann et al. (2009), who prove that in Switzerland, over the period 1988-2004, a one percentage point fall in unemployment rates results in 0.6 percentage points more dual VET positions. Muehlemann et al. (2020) further demonstrate that amidst the negative shock to the economy induced by COVID19, demand for dual VET students and the supply of new dual VET positions have both declined.

Furthermore, in response to the great recession of 2008-9, German firms have tended to reduce individual training activities (Bellmann et al., 2016). This has persisted over the years following the great recession (Dietz and Zwick, 2019). Amidst adverse economic shocks, firms' focus shifts towards avoiding financial distress and training may be treated as a superfluous activity on which to diminish expenses (Brunello and Wruuck, 2020). This results in firms cutting training amidst downturns (NATFHE and Youthaid, 1993), notably when unemployment is rising (Majumdar, 2007). As unemployment rises, Askilden and Nilsen (2005) and Muehlemann and Strupler Leiser (2018) notice that it is relatively easier and cheaper to directly hire skilled workers, who have less alternative options concerning job offers as labour markets are relatively loose. The authors affirm that firms tend to directly hire skilled workers instead of training apprentices, which tends to be a more costly option. Concordant with abovementioned studies, Askilden and Nilsen (2005) find that training responds to the business cycle in a procyclical manner, whilst Dietrich and Gerner (2007) show more specifically that firms' extensive margins (probability to train) tend to increase proportionally to economic growth.

2.2. The Countercyclicality of Training Provision

On the other hand, in support of the income effect's domination in the business cycle – training relationship, Brunello and Bertoni (2021) assert that in advanced economies, such as Switzerland or European Union countries, the magnitude of the substitution effect in this context diminishes. Indeed, financial constraints amidst recessions may not be as binding for firms located in the aforementioned countries as for firms located in developing countries. Not only may firms located in advanced economies have a liquidity buffer, but governments of these countries may intervene to provide support to the economy (see Pleninger et al., 2022, for Switzerland). Consequently, in advanced economies, in the context of the relationship between the supply of dual VET positions and economic activity, the income effect may prevail over the substitution effect. Merrilees (1983) for instance shows that in the United Kingdom, over the 1970s late 1960s, training was negatively related to firms' short-run production dynamics, as firms striving to rashly increase output shift focus from training to manufacturing and final product construction.

Amidst economic downturns, labour becomes relatively cheaper (Schwandt and von Wachter, 2018), therefore firms may have an incentive to increase training provision in order to secure their labour force while it is still affordable (i.e. before economic recovery and a potential labour market tightness increase). Competition also increases during recessions, prompting firms to differentiate themselves from others through quality to gain market share (Felstead and Green, 1994). This may incentivise firms to increase training during economic slumps.

Additionally, there exist "adjustment" costs for firms to renew their labour inputs that may moderate labour demand dynamics over business cycle phases (Taylor, 1979). Therefore profit-maximising firms may be prone to labour hoarding amidst downturns (Nickell, 1986) for multiple reasons, potentially leading training provision to be countercyclical or acyclical. Firms may wish to maintain worker morale by avoiding downsizing or changing the composition of work teams, and thus leave labour inputs untouched at the risk of incurring temporary losses during recessions (Taylor, 1979). Furthermore, firms may respond much more strongly to their expectation of future product demand rather than contemporaneous business cycle fluctuations, again dampening the potential procyclicality of training provision. Finally, firms may use labour hoarding as a form of signalling to its workers, build goodwill and reduce quit rates (Mangan, 1981).

Consequently, considering extant literature, we formulate two conflicting hypotheses:

H0: Swiss firms reduce training as unemployment rises, as this indicates an economic downturn.

H1: Swiss firms increase training as unemployment rises, as training tends to increase amidst downturns.

3. Data

In this section, we first discuss the respective sources of our dependent variable and regressors of interest, subsequently expanding on the construction of our dependent variable. We then describe the data analysed in section 4.

3.1. Data Sources

As our dependent variable, we employ data stemming from Apprenticeship Pulse surveys, conducted monthly between April 2020 and September 2022 by the Chair of Education Systems of the ETH Zurich in collaboration with the Yousty apprenticeship platform. We do not include the months of July 2022 nor August 2022, as the Apprenticeship Pulse survey was not conducted during those months. Furthermore, the recruitment season for dual VET students in Switzerland occurs solely between January and September (inclusive) each year, thus we exclude the months of October to December. In our analysis, we therefore solely exploit variation within recruitment seasons.

Survey respondents were asked each survey wave for the number of vacant and filled positions they offer for the upcoming recruitment period. As we observe it in the data, this variable, which we refer to as "NewPositions", varies with respondent, canton and time, or with respondent, occupation and time. Within survey respondent, sector of activity is time-invariant. In order to reflect all inherent sources of variation in "NewPositions" (survey respondent, occupation, canton, recruitment season and month), we code the variable as follows:

1. For all possible combinations of occupations and canton (25 occupations and 26 Swiss cantons and Liechtenstein), we create a new variable equal to the product of the number of new positions in a given canton and the number of new positions in a given occupation. This yields 675 combinations: pairs of cantons multiplied by occupations. We exclude from our estimation sample respondents who offer 0 new dual VET positions throughout all of their observations. Survey respondents are asked for the number of newly supplied dual VET positions in each occupation and canton separately. Consequently, in order to generate the number of new dual

VET positions in a given occupation within a given canton, we must assume that the distribution of new dual VET positions amongst occupations in constant, or uniform, across cantons (or vice versa, equivalently). One could also state this proportionality assumption as follows: within cantons, each occupation is given the same weight in the calculation of new dual VET positions.

2. For each survey respondent and month in our dataset, we then calculate the sum of new dual VET positions.
3. Finally, we divide the results obtained in step 1 by the results obtained in step 2. This is the dependent variable employed in our analysis.

Our dependent variable is therefore the sum of vacant and filled newly offered dual VET positions reported by respondent i in occupation o, canton c, for recruitment season (year) t and in month m. It does not assume only integer values but remains a genuine count variable.

We source our principal explanatory variable, unemployment, from Switzerland's State Secretariat for Economic Affairs (SECO, 2022). SECO (2021) defines unemployment as the number of jobseekers registered at regional job centres at the end of a given month. Jobseekers that are not unemployed also figure in these numbers, in addition to jobseekers in temporary employment, or job centre dispensed training programmes. Unemployment figures we employ are sectoral, cantonal and monthly, reflecting the three sources of variation of our independent variable. Twenty-one sectors exist and are defined through the "NOGA" classification[4]. Our dependent variable and main regressor have observations in all aforementioned sectors, apart from "activities of extraterritorial organisations and bodies".

The business situation indicator is collected monthly by the KOF Swiss Economic Institute (KOF, 2022). Companies are asked a set of questions, including a request to assess their current business situation on a scale ranging from "poor", "satisfactory", and "good". The net balance of "good" less "bad" assessments is then computed and reflected in the below described variable[5]. The KOF business situation indicator varies across sector and month. Appendix table A4 summarises sectors (according to the NOGA classification) according to their coverage status by the business situation indicator. According to FSO (2022) data, the majority of sectors contributing most towards the creation of added value in Switzerland are covered by the business indicator (e.g. manufacturing, financial and insurance activities, tertiary sector other services, human health and social work activities), with the notable exceptions of "Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles" as well as "Public Administration and Defence".

[4] See https://www.kubb-tool.bfs.admin.ch/en.
[5] This indicator is further interpreted by the KOF in light of current events, see https://kof.ethz.ch/en/news-and-events/kof-bulletin/kof-bulletin/2022/12/Business-situation-slightly-less-encouraging-than-in-previous-month.html.

3.2. Descriptive Statistics

This subsection serves to discuss the summary statistics of our dependent variable and explanatory variable of interest, as well as to visually depict and strive to identify sectoral and geographical sources of variation in our data. Descriptive statistics are shown for our estimation sample.

Table 1 shows descriptive statistics for our dependent variable, in addition to two regressors used: unemployment and the business situation indicator. On average, respondents report a strictly positive number of newly offered dual VET positions for occupation o in canton c, recruitment season r and month t. Variation in new dual VET positions is nonetheless attenuated by the large number of zeros (respondent-occupation-canton-month cells are equal to 0). Furthermore, our dependent variable, driven by the large proportion of respondent-occupation-canton-month cells containing zeros, is heavily positively skewed and leptokurtic, thus is not normally distributed. Its distribution is akin a Poisson distribution with an infinitesimally small mean parameter.

The unit of measurement of our first regressor of interest, unemployment, is 1,000s of individuals. On average, our regressor of interest is equal to 0.555, meaning that on average in a given sector, canton and month, 555 individuals were unemployed as per the definition of SECO (2021). Our second regressor of interest is the KOF's business situation indicator. Its average over our sample is positive, indicating relative optimism of Swiss companies regarding their business situation on average; a higher percentage of respondents considered their business situation to be "good" rather than "bad". The indicator, averaged across all sectors, plummeted at the onset of the COVID19 crisis, before rapidly recovering and peaking at 30 points in August 2022. This explains its relatively substantial standard deviation.

The very low standard error of the mean – substantially lower than the standard deviation – for all three variables reported in table 1 is consistent with the large size of our sample. The sample means of the variables are accurate estimates of respective population means.

Table 1: Descriptive Statistics – Respective Estimation Samples

Variable	**Mean**	**Standard Error of the Mean**	**Observations**	**Minimum**	**Maximum**
Dependent Variable					
New Dual VET Positions	0.058 [0.784]	0.0007	1,033,846	0	284
Regressors of Interest					
Unemployment (in 1,000s of individuals)	0.555 [0.652]	0.0006	1,033,846	0	4.364
Business Situation Indicator	8.733	0.0414	396,459	-71.19	63.31

	[29.82]				

Note: In the "Mean" column, standard deviation is in square brackets. The estimation sample for the business situation indicator is smaller as the latter solely covers ten out of twenty-one sectors according to the NOGA classification.

4. Empirical Methodology

This section discusses our multiple estimation strategies, reviewing their respective robustness. We report results emanating from two distinct econometric methods: linear multi-way fixed effects models with high dimensional fixed effects and pseudo-Poisson maximum likelihood with high dimensional fixed effects estimation. Taken together, our vectors of fixed-effects are highly dimensional as they are proportional to sample size; the number of groups included in the fixed-effects increases with the size of our sample (Guimaraes and Portugal, 2011).

4.1. Baseline Specification

Our preferred specification, executed using multi-way fixed effects (Correia, 2017), is:

$$NewPositions_{ioct} = \alpha_{ioc} \times D_r + \beta_1 Unemployment_{ict} + \theta_{ot} + \mu_{ct} + \gamma_{it} + \varepsilon_{ioct} \qquad (1)$$

θ_{ot} and γ_{it} are vectors of occupation-by-month and respondent-by-month fixed-effects respectively, allowing time shocks to be occupation and respondent-specific (given the configuration of our data, respondent and sector indicators are perfectly collinear; sectors do not vary within respondents, thus we denote sector with the respondent subscript, i). μ_{ct} are canton-by-month fixed effects. ε_{ioct} is the disturbance term. α_{ioc} are respondent-by-occupation-by-canton fixed effects, D_r corresponds to a recruitment-season dummy, assuming the value of one for recruitment season r, 0 otherwise. There are three recruitment seasons; we exploit variation within each recruitment season. The recruitment season, as previously reviewed, takes place over the nine first months of each calendar year. $NewPositions_{ioct}$ is the number of new dual VET positions reported by respondent i, occupation o, canton c, for month t. Our main regressor, $Unemployment_{ict}$, denotes the number, in thousands, of individuals unemployed in the sector of survey respondent i, canton c and month t. It is defined following the definition of SECO (2021), reviewed above. Methodology outlined in Correia (2017) allows for the iterative elimination of singleton groups in our data, improving computational efficiency and the accurate estimation of cluster-robust standard errors. Furthermore, this methodology avoids the application of a double penalty when computing degrees of freedom whenever fixed effects are nested within clusters (i.e. when the clustering variable is identical to or coarser than the fixed effects).

One limitation in our methodology may be highlighted by the keen reader; we have not accounted for the non-random strict positiveness of the dependent variable. Firms recruiting dual VET students do not do so at random as they self-select into recruitment decisions. We nonetheless assume that factors leading to the self-selection of firms into training have been captured by the fixed-effect vectors included in equation (1), so that they should not confound our estimation of β_1 (Wooldridge, 1995).

4.2. Poisson Pseudo-Maximum Likelihood Estimation

Albeit our dependent variable contains non-integer values, it effectively remains count data, enabling the use of Poisson regression (Dahlander et al., 2016). In addition to linear regression with high dimensional fixed effects, we thus also resort to pseudo-Poisson maximum likelihood (PPML) estimation with high-dimensional fixed-effects (Gourieroux et al., 1984, Correia et al., 2020). This methodology is deemed relatively more appropriate in this context given the extreme positive skew of our data (Dahlander et al., 2016, Cupal et al., 2015, Green, 2021). A Poisson distribution with a very low mean parameter (in its absolute value) would indeed fit the distribution of our dependent variable relatively well. PPML-produced standard errors, adjusted for heteroscedasticity and intra-cluster dependence, remain consistent even if the underlying data generating process does not follow a Poisson distribution (Gourieroux et al., 1984). The truncation of our dependent variable below zero further justifies our recourse to PPML, given that such a situation leads to the violation of OLS conditional exogeneity assumptions.

Nonetheless, in our case, PPML with high dimensional fixed effects may be prone to the incidental parameter problem (Neyman and Scott, 1948). Weidner and Zylkin (2021) demonstrate that in gravity models, PPML estimator with three-way fixed effects remains asymptotically consistent for a fixed number of time periods and a number of clusters tending towards infinity. Nonetheless, the PPML estimator will remain asymptotically biased, i.e. converging towards the true value “at an angle”. This asymptotic bias may worsen if the researcher increases the dimensionality of fixed effects included in the analysis. In this context, the incidental parameter problem will also cause cluster-robust standard errors to suffer from a downwards bias, which however negatively depends on the number of clusters in the data. Consequently, we remain cognisant of this issue as we interpret PPML model results.

The baseline PPML equation, employing PPML methodology outlined by Correia et al. (2020) is:

$$E(NewPositions_{ioct}) = \exp\left(\alpha_{ioc} \times D_r + \beta_1 UnemploymentRate_{ict} + \theta_{ot}\right)\varepsilon_{ioct} \qquad (2)$$

θ_{ot} are occupation-by-month fixed-effects. Overdispersion, occurring when the conditional variance exceeds the conditional mean, may be of concern. However, given that our principal objective is to estimate coefficients and test their significance, the use of a PPML model suffices (Santos Silva and Tenreyro, 2006); we do not resort to a negative binomial model in order to address any potential overdispersion (Blackburn, 2015). PPML estimators are well-behaved, even in the presence of a large fraction of zeros in the dependent variable (Santos Silva and Tenreyro, 2006). Moreover, the inclusion of fixed effects substantially mitigates overdispersion.

The estimation sample used in PPML specifications nonetheless differs from samples employed in linear, multi-way fixed-effect analysis. This alone may cause divergence in results emanating from both models. The sample employed in PPML analysis is indeed comparatively smaller as observations separated by a fixed effect are eliminated to allow the convergence of the estimators (see Correia et al., 2020 for a detailed explanation of the separation mechanism and its implications for the convergence of PPML estimators). Equation (2) is the most complex equation that we could execute using PPML with highly dimensional fixed effects, as the algorithm designed by Correia et al. (2020) solely allows for a given number of iterations in the search for separated observations.

4.3. Aggregated Estimation – Relaxing the Proportionality Assumption

We now incorporate the KOF's business situation indicator into estimations; see equations (3) and (4) below. Consequently, whenever the business situation indicator is used as a regressor, our sample reduces to the sectors listed as "covered by the business situation indicator" in appendix A4. Equations (3) and (4) are performed on the same dataset as that described in section 3 (albeit on a subset of sectors), however aggregated such that it now varies over survey respondent, canton, and month[6], as is observed in our data before applying the steps listed in subsection 3.1. We must omit the sector-by-month fixed-effects vector as it would be perfectly collinear with the business situation indicator.

$$NewPositions_{ict} = \alpha_{ic} \times D_r + \beta_1 Unemployment_{ict} + \mu_{ct} + \beta_2 BusinessSituation_{it} + \varepsilon_{ict} \qquad (3)$$

Equation (4) is an investigation into the heterogeneity of the effect of unemployment, as well as the KOF business situation indicator, on training provision. We sequentially interact the two aforementioned regressors with the sectoral indicators mentioned in subsection 3.1, with manufacturing being the comparison group. There are nine such sector indicators included in equation (4).

$$NewPositions_{ict} = \alpha_{ic} \times D_r + \beta_1 Unemployment_{ict} + \mu_{ct} + \beta_2 BusinessSituation_{st} + \beta_i Unemployment_{sct} * Sector_i + \beta_j BusinessSituation_{st} * Sector_i + \varepsilon_{ict} \qquad (4)$$

$$\forall i = 3, \ldots, 9, \forall j = 4, \ldots, 9 \ \forall s = 2, \ldots, 9$$

Equation (5) further investigates heterogeneity by classifying NOGA sectors according to knowledge-intensiveness. According to Balaz (2004), knowledge-intensive sectors are predominant amongst sectors creating and diffusing knowledge, notably using digital technologies. They allow increases in output capacity and link customers, businesses that develop tacit knowledge, and the scientific community, which tends to develop codified knowledge. In the Swiss economy, Arvantis et al. (2017) classify the following sectors as knowledge-intensive: information and communication, financial and

[6] As described in section 3, in our "raw", unprocessed data we observe our dependent variable, the number of dual VET positions, varying by survey respondent, canton and month. For equations (3) and (4), we need not assume the proportionality rule enunciated in subsection 3.1.

insurance activities and manufacturing[7]. Following Balaz (2004), we also classify real estate activities as knowledge-intensive. Equation (5) is:

$$NewPositions_{ict} = \alpha_{ic} \times D_r + \beta_1 Unemployment_{ict} + \mu_{ct} + \beta_2 BusinessSituation_{it} + \beta_i Unemployment_{sct} * KIBS_i + \beta_j BusinessSituation_{st} * KIBS_i + \varepsilon_{ict} \quad (5)$$

Where KIBS denotes knowledge-intensive business services, which we assimilate to knowledge-intensive sector.

4.4. <u>Standard Errors</u>

To determine the optimal level of clustering for standard errors, we face the following trade-off: for the achievement of valid asymptotic inference, we must maximise the number of clusters, such that it tends towards infinity. This would however entail the choice of finer clusters. However, should observations be correlated at a coarser level than that at which standard errors are clustered, asymptotic inference based on the t-distribution and Wald test statistics may substantially over-reject null hypotheses. The levels of clustering we consider are as follows: survey respondent, occupation, occupation-by-canton. Table A3 reports, as recommended by MacKinnon et al. (2022), descriptive statistics concerning the number of observations for each of the three clustering variables.

MacKinnon et al. (2022) state that the quality of asymptotic inference (here, measured by the rate of false null hypothesis rejections) decreases as clusters become less homogenous (in terms of number of observations per cluster). Table A3 shows that the most homogenous potential clustering variable, as measured by the ratio of variance to the mean, is survey respondent. Moreover, there are 5,150 survey respondent clusters for equation (1), over 25 times larger than the number mentioned by MacKinnon et al. (2022) for inference based on the t(G-1) in unfavourable cases to remain unreliable (with G corresponding to the number of clusters). We thus cluster our standard errors by survey respondent, using so-called “CV1” cluster-robust standard errors.

[7] We classify the manufacturing sector as a whole as knowledge-intensive because we cannot identify more granular subsections. Arvantis et al. (2017) state, for Switzerland, that “in the manufacturing sector there are more high-tech (e.g. chemicals, pharmaceuticals, electrical equipment) than low-tech firms (66% vs 34%)”.

5. Results

This section serves to present and interpret our results in line with our hypotheses and extant literature. We subsequently present robustness checks using alternative estimation methods introduced in section 4, before discussing the investigation into heterogeneity in the effect of the business cycle on the supply of dual VET positions.

5.1. Baseline Results

Table 2 displays results from multi-way fixed-effects models in all columns apart from column 1, which displays results from a pooled OLS model without any fixed-effects. In section 3.1, we have described the proportionality assumption made in order to construct our dependent variable employed in all estimations reported here.

Our preferred specification is displayed in column (6) and corresponds to equation (1). This specification controls for the largest amount of unobserved heterogeneity, allowing an accurate identification of the coefficient estimated on the unemployment regressor. The inclusion of canton-by-time fixed effects is particularly important, as they control for potentially asymmetrical population dynamics across cantons. The number of compulsory school leavers in each yearly cohort acts as a mediator in the training – business cycle relationship (Luethi and Wolter, 2020), potentially exacerbating a downturn's impact on the number of newly offered dual VET positions. Muehlemann et al. (2009) similarly assert that demographic change is a key driver of the supply of dual VET positions.

Regardless of the fixed-effects vectors included in the analysis, as well as the various interactions between fixed-effects vectors permitted by our multiple sources of variation, all models conducted using fixed-effect methodology lead to the identical conclusion. In Switzerland, over our sampled period, training is acyclical; unemployment is insignificantly negatively associated with the provision of dual VET positions[8].

[8] To suppress any potential problem of reverse causality, we also execute the specification in column (5) using unemployment lagged by one month. Results are qualitatively quasi-identical and can be produced upon request.

Table 2: Regression Results

Dependent Variable: Newly offered dual VET positions	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment (in thousands of individuals)	0.0723***	-0.0263	-0.0290	-0.0321	-0.0415	-0.0574
	(0.00707)	(0.0203)	(0.0362)	(0.0359)	(0.0433)	(0.0619)
Observations	1,033,846	1,033,846	1,033,846	1,033,846	1,033,846	1,033,846
Adjusted Within R-squared	0.003	0.000	0.000	0.000	0.000	0.000
Respondent-by-occupation-by-canton FE	No	Yes	No	No	No	No
Respondent-by-occupation-by-canton-by-recruitment-season FE	No	No	Yes	Yes	Yes	Yes
Recruitment-season FE	No	Yes	No	No	No	No
Month FE	No	Yes	No	No	No	No
Sector-by-month FE	No	No	Yes	No	No	Yes
Canton-by-month	No	No	No	No	Yes	Yes
Occupation-by-month FE	No	No	No	Yes	No	Yes

Note: Robust standard errors in parentheses, clustered by survey respondent in all columns. *** p<0.01, ** p<0.05, * p<0.1. In all specifications, the dependent variable is the number of newly offered dual VET positions reported by respondent i in occupation o, canton c, sector s and month t in recruitment season r. The main regressor, unemployment, is sector-canton-month specific. Column 1 displays results from a pooled OLS specification, whilst all other columns display results from multi-way fixed-effects estimations using methodology outlined in Correia (2017). Column 1 displays the overall adjusted R-squared rather than the adjusted within r-squared.

5.2. Poisson Pseudo-Maximum Likelihood Estimation

Table A1 of the appendix displays results from PPML estimation with high-dimensional fixed-effects, with a specification corresponding to equation (2). Albeit the magnitude of the estimated effect of unemployment on the supply of dual VET positions is substantially larger than the magnitude of the estimates displayed in column (2) of table 2, the standard errors are considerably large as well. PPML estimation thus leads us to the same inference: a rise in unemployment is insignificantly negatively associated with training provision. Due to this insignificance, we cannot provide any robust support for either hypothesis H0 or hypothesis H1.

5.3. Results Employing the Aggregated Dataset

As stated in subsection 3.1, we do not observe $NewPositions_{ioct}$, however we obtain it through a proportionality assumption. Given that this proportionality assumption may be driving the significance in our results, we also conduct estimations with $NewPositions_{ict}$, which we actually observe in our data. Table 3 presents results of equation (3) (discussed in section 4.3) in the fifth column. While conducting analysis on our aggregated dataset, column (5) of table 3 is our preferred specification for the simultaneous inclusion of both proxies for the business cycle; unemployment and the business situation indicator. Column (3) is our preferred specification for the sole inclusion of unemployment as a regressor, whilst column (4) depicts our preferred specification regarding the inclusion of the business situation indicator as sole regressor. Both proxies of the business cycle are individually statistically insignificant at the 5% level in columns (3) and (4), in addition to being individually as well as jointly insignificant in column (5)[9]. Consequently, we infer that the proportionality assumption described in section 3.1. and imposed in equation (1) was not the significant driver of our insignificant results. We are thus confident that after accounting for the fixed effect vectors elicited in equations (1) and (3), unemployment negatively, albeit insignificantly, impacts the supply of dual VET positions. The sign of the impact of the business situation indicator on the supply of dual VET positions is less clear, nonetheless we cannot refute the hypothesis of no significant effect of the former on the latter.

[9]A Wald test was conducted in order to test the joint statistical significance of the unemployment and the business situation indicator regressors. The Wald test statistic is 0.55, corresponding to a p-value of 0.5757.

Table 3: Business Situation Indicator and Unemployment (Aggregated on ICT Level)

Dependent Variable: Newly offered dual VET positions	(1)	(2)	(3)	(4)	(5)
Business Situation Indicator	-0.000551	0.000200		0.000192	0.00017
	(0.000338)	(0.000227)		(0.000222)	(0.00022)
Unemployment (in 1,000s of individuals)	-0.00837	0.00927	-0.0227		-0.02233
	(0.0138)	(0.0140)	(0.0317)		(0.03174)
Observations	396,459	396,459	396,459	396,459	396,459
Adjusted Within R-squared	0.000	-0.000	0.000	-0.000	-0.000
Respondent-by-canton-by-recruitment-season FE	No	Yes	Yes	Yes	Yes
Respondent-by-canton FE	Yes	No	No	No	No
Recruitment Season FE	Yes	No	No	No	No
Month FE	Yes	Yes	No	No	No
Canton-by-month FE	No	No	Yes	Yes	Yes

Note: Robust standard errors in parentheses, clustered by survey respondent in all columns. *** p<0.01, ** p<0.05, * p<0.1. In all specifications, the dependent variable is the number of newly offered dual VET positions reported by respondent i in canton c and month t in recruitment season r. The main regressors, unemployment and the business situation indicator, are respectively sector-canton-month and sector-month specific. All columns display results from multi-way fixed-effects estimations using methodology outlined in Correia (2017).

5.4. Heterogeneity Analysis

Appendix table A2 displays the results of equation (4) in its third column, constituting our investigation into potential heterogeneity in the relationship of training provision and the business across sectors. In column (1), we exclude unemployment from the specification and interact the business situation indicator with nine sectors[10], leaving manufacturing as the base group. Column (2) contains the unemployment regressor, included alone and interacted with the identical nine sectors as listed in column (1). Finally, column (3) of appendix table A2 depicts results obtained from equation (4), in which both the business situation indicator and the unemployment regressors are included, each interacted with nine sectors. Manufacturing remains the base group. In all three aforementioned

[10] These nine sectors are transportation and storage, construction, hospitality, information technology (IT), real estate, administrative and support services, human health and social work, arts, entertainment and recreation, and finally finance and insurance. See appendix table A4.

specifications, no coefficient is significant at the 5% level apart from the interaction between the business situation indicator and the construction sector dummy variable in column (3). This interaction term is statistically significant at the 1% level and negative, suggesting that a rise in the business situation indicator has a significantly more negative effect on the supply of dual VET positions in the construction sector than in the manufacturing sector.

We now turn to equation (5), depicted in the third column of table 4. Table 4 depicts the results of our second investigation into sectoral heterogeneity between KIBS and non-KIBS sectors, described at the end of subsection 4.3. Column (1) of table 4 displays results of a specification in which, fixed-effects vectors aside, solely unemployment, the KIBS sector indicator variable and the interaction between both aforementioned regressors are included. Column (2) follows the identical logic, however replacing unemployment with the business situation indicator. Coefficients on all three interaction terms depicted in table 4 are statistically insignificant, pointing towards a lack of heterogeneity across sectors in the effect of the business cycle on the supply of dual VET positions.

Table 4: Heterogeneity Across KIBS Sectors

Dependent Variable: Newly offered dual VET positions	(1)	(2)	(3)
Unemployment (in 1,000s of individuals)	-0.0221		-0.0231
	(0.0314)		(0.0322)
Business Situation Indicator		5.98e-05	-2.07e-05
		(0.000280)	(0.000324)
KIBS Sector	0.0418	0.0311	0.0415
	(0.0425)	(0.0331)	(0.0421)
Business Situation Indicator * KIBS Sector		0.000211	0.000238
		(0.000335)	(0.000428)
Unemployment * KIBS Sector	-0.0277		-0.0194
	(0.0470)		(0.0499)
Observations	396,459	396,459	396,459
Adjusted Within R-squared	-0.000	-0.000	-0.000
Respondent-by-canton-by-recruitment-season FE	Yes	Yes	Yes
Canton-by-month	Yes	Yes	Yes

Note: Robust standard errors in parentheses, clustered by survey respondent in all columns. *** p<0.01, ** p<0.05, * p<0.1. In all specifications, the dependent variable is the number of newly offered dual VET positions reported by respondent i in canton c and month t in recruitment season r. The main regressors, unemployment and the business situation indicator, are respectively sector-canton-month and sector-month specific. All columns display results from multi-way fixed-effects estimations using methodology outlined in Correia (2017).

Consequently, we have very limited empirical evidence to support any of our two hypotheses developed in section 2. In addition, the magnitude of the investigated relationship between the business cycle and the supply of dual VET positions is likely modest. Consequently, our results are discordant to those of Muehlemann et al. (2020) and Luethi and Wolter (2020), however are in line with the findings of Felstead and Green (1994) and Brunello and Bertoni (2021). In line with the observation of Baldi et al. (2014) and Muehlemann et al. (2009), the magnitude of the effect of business cycle fluctuations on the supply of dual VET positions is relatively small, with other factors such as demographic change presumably playing a much more important role in the determination of dual VET positions supply.

Conclusion

Labour markets for dual VET positions worldwide have faced tumultuous times since the start of the COVID19 pandemic and the ensuing exceptionally tight labour markets. This paper contributes to the strand of literature concerned with the response of training provision to changes in the business cycle. We have sought to produce empirical evidence eliciting the effect of the business cycle, proxied by unemployment and subsequently the business situation indicator, on training provision in Switzerland. This paper, at the time of writing, is the first to consider five sources of variation in training provision: respondent, occupation, canton, recruitment season and month, whilst also considering three sources of variation in a proxy of the business cycle - unemployment: sector, canton and month. The inclusion of interacted fixed effects permitted by the rich data employed in this study thus substantially mitigates the risk of confounding through omitted variable bias.

Our results do not provide robust evidence that the provision of dual VET positions responds significantly to business cycle fluctuations. In all main specifications, unemployment, as well as the business situation indicator, both individually and jointly, have an insignificant effect on training provision. Our results thus do not lend support to hypothesis H0, neither do they support hypothesis H1. Furthermore, we fail to find substantial sectoral heterogeneity in the cyclicality of dual VET positions supply, aside from the construction sector, in which the business situation indicator (reflecting Swiss firms' sentiment regarding economic outlook) has a significantly more negative impact on training provision than in the manufacturing sector. The knowledge-intensiveness of a sector does not seem to significantly affect the business cycle-training provision relationship.

The absence of significant cyclicality in the supply of dual VET positions bears policy implications. Swiss training firms facing headwinds in the form of adverse business cycle fluctuations do not appear to reduce training, as the income effect seems to offset the substitution effect in the business cycle – training relationship. Consequently, training subsidies granted to firms or any exceptional regulatory changes amidst downturns aimed at safeguarding training provision are likely to be superfluous in

Switzerland. The effectiveness of training subsidies on the provision of training could be investigated in future research.

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APPENDIX

Table A1: PPML Estimation with High Dimensional Fixed Effects

Dependent Variable: Newly offered dual VET positions	(1)	(2)
Unemployment (in thousands of individuals)	-0. 225 (5.823)	-0.192 (6.205)
Observations	53,346	53,346
Residual Degrees of Freedom	5,394	5,394
Deviance	45,078.40	47,056.34
Month Fixed-Effects	Yes	No
Canton-by-Month Fixed-Effects	No	Yes
Occupation-by-Month Fixed-Effects	No	No
Sector-by- Month Fixed Effects	No	No
Respondent-by-Occupation-by-Canton-by-Recruitment-Season Fixed Effects	Yes	Yes

Note: Robust standard errors in parentheses, clustered by survey respondent in all columns. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the number of newly offered dual VET positions reported by respondent i in occupation o, canton c, sector s, recruitment season r and month t. Results displayed in this table stem from a Poisson pseudo maximum likelihood estimation, following methodology outlined in Correia et al. (2020). The marginal effect, rather than a regression coefficient, is depicted here. The variance-covariance matrix estimator follows the unconditional computation, allowing for heteroscedasticity and other violations of distributional assumptions, such as dependence of observations.

Table A2: Heterogeneity Analysis

Dependent Variable: Newly offered dual VET positions	(1)	(2)	(3)
Unemployment (in thousands of individuals)		-0.0282 (0.0566)	-0.0491 (0.0678)
Business Situation Indicator	1.91e-05 (0.000371)		-0.000283 (0.000390)
Business Situation Indicator * Construction	-0.00118* (0.000640)		-0.00206*** (0.000795)
Business Situation Indicator * Transport and Storage	-0.00491 (0.00529)		0.0110 (0.0117)
Business Situation Indicator * Accommodation and Food Service Activities	0.000167 (0.000353)		0.000300 (0.000418)
Business Situation Indicator * Information and Communication	0.000753 (0.000744)		0.00124 (0.000879)
Business Situation Indicator * Financial and Insurance Activities	-0.000530 (0.000834)		-0.000120 (0.000800)
Business Situation Indicator * Real Estate Activities	0.000327 (0.000617)		0.000381 (0.000952)
Business Situation Indicator * Administrative and Support Services	0.000156 (0.00109)		0.000621 (0.00114)
Business Situation Indicator * Human Health and Social Work	0.000275 (0.00101)		0.000595 (0.00117)
Business Situation Indicator * Arts, Entertainment and Recreation	-0.000117 (0.000401)		0.000530 (0.000706)
Unemployment * Construction		0.0176 (0.0425)	0.0113 (0.0505)
Unemployment * Transport and Storage		2.722 (2.813)	3.136 (3.246)
Unemployment * Accommodation and Food Service Activities		-0.00422 (0.0408)	0.0167 (0.0514)
Unemployment * Information and Communication		0.101 (0.258)	0.178 (0.307)

Unemployment * Financial and Insurance Activities		0.233 (0.213)	0.238 (0.209)
Unemployment * Real Estate Activities		-1.304 (2.112)	-1.326 (2.154)
Unemployment * Administrative and Support Services		0.221 (0.333)	0.262 (0.364)
Unemployment * Human Health and Social Work		-0.0634 (0.281)	-0.0540 (0.283)
Unemployment * Arts, Entertainment and Recreation		0.820 (1.316)	1.024 (1.522)
Observations	396,459	396,459	396,459
Number of clusters	2,868	5,140	2,868
Adjusted Within R-Squared	-0.000	0.000	0.000
Respondent-by-canton-by-recruitment-season FE	Yes	Yes	Yes
Canton-by-month	Yes	Yes	Yes

Note: Base group is manufacturing. Robust standard errors in parentheses, clustered by survey respondent in all columns. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable in all specifications is the number of newly offered dual VET positions reported by respondent i in canton c, sector s, and month t in recruitment season r.

Table A3: Descriptive Statistics – Number of Observations Per Potential Clustering Variable

Potential Clustering Variable	**Mean Number of Observations per Cluster (Mean)**	**Number of Clusters**	**Number of Observations in Smallest Cluster (Minimum)**	**Number of Observations in Largest Cluster (Maximum)**	$\frac{Standard\ Deviation}{Mean}$	$\frac{Maximum}{Mean}$
Survey Respondent	609.126 [655.104]	5,150	42	3,822	1.08	6.2746
Occupation	41,311.18 [50,620.08]	214	63	165,835	1.225	4.01429
Occupation-by-Canton	1,967.2 [2,410.48]	4,494	3	7,897	1.225	4.01434

Note: In the “Mean” column, standard deviation is in square brackets.

Table A4: NOGA Sectors According to Their Coverage Status by the Business Situation Indicator

NOGA Sector	Covered by Business Situation Indicator	Not Covered by Business Situation Indicator
Agriculture, Forestry and Fishing		X
Mining and Quarrying		X
Manufacturing	X	
Electricity, Gas, Steam and Air-Conditioning Supply		X
Water Supply, Sewerage, Waste Management and Remediation Activities		X
Construction	X	
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles		X
Transportation and Storage	X	
Accommodation and Food Service Activities	X	
Information and Communication	X	
Financial and Insurance Activities	X	
Real Estate Activities	X	
Professional, Scientific and Technical Activities		X
Administrative and Support Service Activities	X	
Public Administration and Defence		X
Education		X
Human Health and Social Work Activities	X	
Arts, Entertainment and Recreation	X	
Other Service Activities		X
Activities of Households as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Use		X
Activities of Extra-territorial Organisation and Bodies*		X

*This sector is completely absent from our data.