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Andreas F. Bühler, Patrick Lehnert and Uschi Backes-Gellner

Universität Zürich
IBW – Institut für Betriebswirtschaftslehre

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Curriculum Updates in Vocational Education and Changes in Graduates' Skills and Wages*

Andreas F. Bühler[1], Patrick Lehnert[2] & Uschi Backes-Gellner[3]

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Abstract: This paper examines how the nature of curriculum updates of vocational education and training (VET) changes VET graduates' occupational skill bundles and wages. Using VET curriculum texts as data, we apply natural language processing methods to identify the nature of changes in curriculum updates. We introduce and measure two dimensions of curriculum updates: the 'novelty rate' (degree of new skills entering an updated curriculum) and the 'removal rate' (degree of old skills being dropped from the old curriculum). By matching this information on VET curriculum updates with labour market data for VET graduates, we empirically investigate how different types of curriculum updates change the wages of graduates with updated curricula compared to those of graduates with old curricula. We find non-linear relations and complementarities between the dimensions of updates and graduates' wages: the association of the novelty rate with wages is u-shaped whereas the association of the removal rate with wages is inversely u-shaped. Most important are the combined results of adding and removing skills. While adding lots of new skills without removing old ones is not beneficial, removing skills with all kinds of curriculum updates is. A further analysis on the actual skills that are added or removed illustrates the trade-offs that curriculum designers must make.

JEL Classification: I26, J24, M53
Keywords: nature of curriculum updates, changes in skills, vocational education and training, curricula

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[1] Corresponding author. University of Zurich, Department of Business Administration. Email: andreas.buehler@business.uzh.ch. Address: Plattenstrasse 14, 8032 Zurich, Switzerland
[2] University of Zurich, Department of Business Administration. Email: patrick.lehnert@business.uzh.ch
[3] University of Zurich, Department of Business Administration. Email: backes-gellner@business.uzh.ch

1. Introduction

Updating educational curricula always entails several trade-offs. If programme length and training time are fixed – as in almost all study programmes in vocational or academic education – adding new skills comes at the cost of either overloading a curriculum or removing other skills. In addition, for vocational education and training (VET) programmes, which involve training firms, some firms may already need new skills while others may not, causing a second trade-off in curriculum updates: if a curriculum is tailored towards the former firms, i.e. the more innovative ones, it does not entirely meet the requirements of the latter, i.e. the more mainstream ones (see e.g. Schultheiss and Backes-Gellner 2022; Schweri, Aepli, and Kuhn 2021). Moreover, there is a third trade-off as curriculum updates induce adaptation costs for training providers (e.g. firms, schools, teachers), the costs of updates need to be weighed against the benefits accruing from a curriculum update.

A small stream of literature on skills in educational curricula provides first evidence that more up-to-date skills positively affect labour market outcomes. For example, some very specific modern skills in VET curricula such as i) computer numerical control-skill (CNC) or IT skills in general and ii) certain non-cognitive skills affect individual labour market outcomes as shown by (Girsberger, Koomen, and Krapf 2022; Kiener et al. 2022; Kiener, Gnehm, and Backes-Gellner 2023; Eggenberger and Backes-Gellner 2023; Janssen and Mohrenweiser 2023). Moreover, more up-to-date academic curricula positively relate to innovation outcomes and wages of graduates as shown by Biasi and Ma (2022).

However, even though curriculum updates usually involve more than merely adding new skills, the full nature of curriculum updates – i.e. the degree to which curricula are reshuffled and old skills are removed relative to new skills – as well as the effect of such reshufflings on labour market outcomes of graduates has thus far not been analysed. Yet understanding the effects of differences in the nature of curriculum updates is crucial to be able to improve future curriculum updates and to provide valuable insights for educational institutions, industry organisations and firms or other stakeholders that are in charge of curricula and have to deal with the above mentioned three trade-offs.

In this paper, we investigate the nature of curriculum updates by defining two novel proxies for measuring it: the ‘novelty rate’ and the ‘removal rate’. These proxies constitute two independent dimensions of a curriculum update. As updates may add either a few or a great many new skills and at the same time may remove either a few or a great many old skills, a large number of permutations in the updating process are possible. We use text as data from

Swiss VET curricula to study the effects of such curriculum updates because they provide an ideal setting due to a number of advantages. First, two thirds of the Swiss working population (i.e. all middle-skilled workers) obtain their initial skills through dual VET programmes. Second, Switzerland is among the top countries in international innovation rankings (e.g. the World Intellectual Property Organization's Global Innovation Index, see Dutta et al. 2021) meaning that the updating of VET curricula has to be frequent and plays a crucial role in equipping the workforce with the necessary skills for driving productivity and firm innovation (e.g. Rupietta and Backes-Gellner, 2019; Schultheiss and Backes-Gellner, 2022).

Moreover, Swiss VET curricula are well-suited for our analysis for four analytical reasons: First, VET curricula extensively describe all skills that middle-skilled workers must acquire in their respective VET programme. As VET programmes typically last 3-4 years[4], they are comparable in length to many upper secondary schooling programmes in other countries. Second, VET curricula are frequently updated in a systematic and institutionally regulated process that involves important economic actors, particularly firms at the innovation frontier (Backes-Gellner, 1996; Rupietta and Backes-Gellner, 2019). As a result, the updated curricula include the most up-to-date necessary skills (Backes-Gellner and Pfister, 2019). Third, VET curricula are nationally binding, meaning that the training in each occupation must follow the content. Fourth, mandatory assessment procedures for each occupation ensure that students acquire all the skills prescribed in the curricula.[5] The latter two characteristics allow us to assume that the content of each occupational training curriculum actually indicates the skills of the workers who graduate from this occupational program. This assumption is supported by previous studies showing that skills measured in VET curricula are related to the labour market outcomes of VET graduates (Eggenberger, Rinawi, and Backes-Gellner 2018; Girsberger, Koomen, and Krapf 2022; Kiener et al. 2022; Kiener, Gnehm, and Backes-Gellner 2023; Langer and Wiederhold 2023).

We measure the skills in the curricula by applying natural language processing (NLP) methods to the curriculum texts as data and by following Eggenberger and Backes-Gellner (2023). Their procedure allows us i) to identify all single skills in the universe of VET curricula and ii) to measure the relative importance (weights) of each skill in a given curriculum. Using this skill information, we can calculate the changes in skills and their weights between old and

[4] The training takes place in firms (approx. 80 percent of student training time) and in vocational schools (approx. 20 percent of student training time).

[5] Typically, the assessments include both interim and final exams and both a written and a practical part, making them very comprehensive.

updated curricula. With this data, we construct two novel dimensions of curriculum updates: the ‘novelty rate’ (i.e. the share of weighted skills appearing in an updated curriculum but not in the old curriculum) and the ‘removal rate’ (i.e. the share of weighted skills that existed in an old curriculum but did no longer appear in its updated version). To estimate whether and, if so, how such changes in curriculum updates relate to changes in VET graduates’ wages, we combine our proxies for curriculum updates with wages for VET graduates trained under either the old or the updated VET curricula. To measure wages, we use the Social Protection and Labour Market (SESAM) survey from the Swiss Federal Statistical Office.

Our results show that the nature of a curriculum update, i.e. the relation of smaller or larger novelty rates in combination with smaller or larger removal rates, is indeed related to the wages of graduates of these updated programmes. We find i) non-linear relations and ii) complementarities between the two update dimensions and the graduates’ wages: adding only small amounts of new skills to an updated curriculum has a negative effect, which persists until a certain threshold and becomes positive afterwards, i.e. the novelty rate follows a u-shape. In contrast, the removal rate follows an inverse u-shape, thus having a positive effect but at a decreasing rate. However, most important is the effect of the combination of adding and removing more or fewer skills. Here we also find non-linear effects: Adding a great many skills without removing old skills is not beneficial, but if curricula are updated, the removal of skills is always beneficial independent of the particular novelty rate. Thus, introducing new skills into a curriculum should always entail simultaneously removing old skills. This is the most important takeaway from our empirical study, but likely also the takeaway that is most difficult to realise because cherished old skills have to be removed to make room for unknown skills that cause additional costs to teach. This adds another trade-off to any curriculum updating process.

A further analysis on the actual skills that are added or removed illustrates the concrete trade-offs that curriculum designers face. In this analysis, we investigate which skills have actually increased or decreased in weight as a result of all the curriculum updates in our sample from 2005-2015. We find that the group of novel skills that are most largely added across all curricula are generic skills that can be used in any type of occupation and focused technological skills that match the technological changes during the respective time. Examples of such generic skills are social skills, organizational skills, or quality control and safety skills; examples of focused technological skills are control and precision technology skills like CNC, ‘control technology’ or ‘automatization’. At the same the group of skills that are most largely removed from curricula are either ‘narrow manual skills’ or ‘general education foundations’. Examples of the former are ‘model making’ and ‘furniture making’; examples of the latter are ‘chemistry’ or ‘physics’. Empirical results on the wage effects of increases or decreases in these skill categories further illustrate the trade-offs that curriculum designers must make.

These findings have important implications for policymakers and many types of stakeholders involved in any updating of curricula. Striking the right balance between adding new skills to promote innovation and removing old skills to avoid overloading a curriculum is a crucial target for any curriculum designer if we look at our labour market results. The challenge lies in determining the optimal amount of new skills while also removing the corresponding optimal amount of outdated skills.

2. Institutional Setting and Skill Measurement

As we exploit Swiss VET curricula in our curriculum analyses, we first have to provide some important characteristics of the Swiss VET system that are necessary to understand our empirical analyses and conclusions. Second, we describe the structure of VET curricula to be able to explain how we derive our skill measures and how we calculate our two dimensions of curriculum updates, i.e. the ‘novelty rate’ and the ‘removal rate’ (i.e. the differences between old and updated curricula).

2.1 Important Characteristics of the Swiss VET System

Nearly 70% of all Swiss adolescents start their labour market careers with a VET programme in one of the 245 different VET occupations (State Secretariat for Education Research and Innovation 2022). Thus, the VET system in Switzerland is essential for equipping basically all middle-skilled workers with the necessary labour market skills. Students choose their occupation at the age of 15 to 16 and most of them enrol in 3- or 4-year dual VET programmes, depending on the occupation. Only about 10% choose a lower level 2-year programme. Dual VET takes place in two learning locations. First, for roughly 80% of the time, apprentices are trained on the job in firms. Second, for the remaining 20%, apprentices study in a vocational school. For both parts of the training, the occupational training curricula are legally and nationally binding.

The development or updating of curricula in the Swiss VET system has three features that are important for our empirical analyses: i) the regular updating of skills ii) the almost randomness in the concrete timing of a particular occupational curriculum, and iii) the binding nature of the content for all students. First, Swiss VET curricula are updated through a regular, well-defined, and legally mandated updating process (State Secretariat for Education, Research, and Innovation, 2017). A key characteristic of this process is the strong involvement of all relevant actors such as innovative firms; occupational, industry and employers' associations; trade unions; and cantonal and federal government institutions. This updating process ensures up-to-date skills in VET curricula, and a dissemination of the prescribed future-oriented skills through all middle-skilled workers entering the labour market (Backes-Gellner 1996; Backes-Gellner and Pfister 2019; Rupietta and Backes-Gellner 2019; Bolli et al. 2018).

Second, the precise timing of these updates strongly depends on administrative factors such as the capacities of the State Secretariat for Education, Research and Innovation, which coordinates and approves the updates. Thus the exact timing of the updates for different occupations is quasi-random, thereby reducing endogeneity problems in our empirical analyses on the relation between curriculum updates and their labour market outcomes (Schultheiss and Backes-Gellner 2022).

Third, because curricula are mandatory for all firms that train apprentices in an occupation and because quality assessment procedures and interim and final exams are legally binding, we can assume that all VET graduates in a given occupation possess the skills that are listed in the curriculum of that occupation. The system also ensures that an updated curriculum becomes mandatory nationwide for all training entities as soon as it legally takes effect.

2.2 Measuring Skills in Curricula

Our source for capturing curriculum updates is the texts of Swiss VET curricula, from which we extract skills by a natural language processing (NLP) method. Each VET curriculum, typically consisting of 30 to 50 pages and extensively describes the required learning outcomes at three hierarchical levels of goals: i) competence areas, ii) learning objectives, and iii) (operational) learning goals.[6] The third level learning goals specify precisely what skill apprentices need to acquire and have to prove in interim and final examinations to graduate in their occupation. To measure all skills in a curriculum (old or updated) and to calculate our update dimensions, we use the raw texts of the operational learning goals (i.e. we use each item from 1.4.1.1 to 1.4.1.4 in the example for the 'laboratory technician' (Laborant) in **Figure 1** and store them as skill descriptions in the text database that we use for the NLP method).

[6] In German: 1. Leitziele, 2. Richtziele, 3. Leistungsziele

Figure 1: Laboratory technician (example of learning outcomes at three hierarchical levels, abridged)

1st Level Goal (Competence Area) *1.4 Health, safety, environmental protection and quality assurance* Protecting the health of laboratory employees, ensuring the safety of people and the environment and safeguarding quality are of central importance in a laboratory. Laboratory technicians use suitable working techniques and take measures to ensure safety and to avoid or reduce negative effects on the environment. They work preventively and use quality assurance measures to ensure the legally defined and operationally required quality of results and optimisation of resources.
2nd Level Goal (Learning Objective) *1.4.1* Laboratory technicians recognise the importance of company and legal requirements regarding health protection and safety. They dutifully implement measures for self-protection and the protection of third parties.
3rd Level Goals (Operational Learning Goals) 1.4.1.1 Laboratory technicians determine and apply the necessary measures for self-protection and the protection of third parties. 1.4.1.2 Laboratory technicians demonstrate the correct behaviour in the event of an accident and, if necessary, act in accordance with the instructions. 1.4.1.3 Laboratory technicians safely apply fire-fighting measures when necessary. 1.4.1.4 Laboratory technicians apply the legal and company safety regulations, as well as the access regulations.

Notes: – Authors' compilation and translation from German language VET curriculum of the 'laboratory assistant'. Source: State Secretariat for Education Research and Innovation (2007)

For our analyses we use all third level learning goals of the curricula that have been updated in the period between 2005 and 2015. This results in a database with detailed skill descriptions for 390 old and updated occupational training curricula.[7] These 390 curriculum texts have an average of 130 operational learning goals per curriculum, totalling 50,698 operational learning goals. To identify the different single skills mentioned in all the curriculum texts, we use NLP methods following Eggenberger and Backes-Gellner (2023). This methodological approach is based on Eggenberger, Rinawi, and Backes-Gellner (2018), who manually categorised skills, and on Kiener et al. (2022) and Kiener, Gnehm, and Backes-Gellner (2023), who developed a machine learning approach to replace the manual categorisation with NLP methods.

The NLP approach consists of a two-stage procedure. In the first stage, an unsupervised algorithm identifies 258 distinct skill clusters from the 50,698 operational learning goals. In the second stage, we attribute all learning goals of all curricula to these 258 clusters. In doing so

[7] We use all curricula that were at least once completely updated according to the procedure of SERI (2017) in the period between 2005 and 2015 (for details see Backes-Gellner & Pfister 2019) and for which old and new curricula were available as processible texts (almost all).

we follow the same procedure as Eggenberger and Backes-Gellner (2023). Appendix A explains our NLP procedure in detail.

This procedure provides us with a database with detailed information on all the skill clusters that occur in all curricula texts (old or new). For each of the curricula we then count the number of learning goals that belong to one of the 258 skill clusters. As a result, we can calculate the percentage of the learning goals that belong to each of the skill clusters in one occupational curriculum, which we then use as the weights of these skills clusters in the old and new curricula. To illustrate this, we can again use the curriculum of the laboratory assistant (Laborant). We find that 13.9% of all learning goals belong to the skill cluster ‘chemistry’ (Chemie), 8.8% belong to the skill cluster ‘quality insurance’ (Qualitätssicherung), and 6.6% belong to ‘workplace safety’ (Arbeitsplatzsicherheit) and that there are 38 other skill clusters, but all with lower weights.

2.3 Calculating Update Dimensions

We calculate our two updating dimensions ‘novelty rate’ and ‘removal rate’ by comparing the skills in the old and the updated curriculum of the same occupation. To do so we can draw from 88 occupational updates in the given time period (i.e. 176 different curricula composed of 88 pairs of old and updated occupational curricula). We draw these updates as follows from the universe of Swiss VET curriculum updates between 2005 and 2015: First, to ensure similar quality levels, we restrict the sample to 3- and 4-year programmes, i.e. we exclude all two-year programmes. Second, we exclude completely new occupations, i.e. these for which no preceding curriculum exists. Third, we exclude occupations that are not part of the classification in our labour market data, because we later need to match the skills data to less differentiated labour market data and thus cannot use them.

Fourth, when two or more occupations have been merged, we use the old occupation with the largest number of apprentices for calculating the novelty and removal rates of the updated curriculum. By so doing, we ensure that every updated curriculum corresponds to only one old curriculum and receives only one novelty rate and one removal rate.[8] Fifth, we exclude from our curriculum updates the few very small occupations for which we have no observations both before and after the update, because we cannot use them later in the labour market analysis.

[8] While this restriction adds noise to our data, we cannot use different novelty and removal rates in our analysis of labour market outcomes.

As the occupations that we do use in our analysis are the most frequently chosen occupations, our data represent about 90% of all VET graduates in Switzerland.

To measure the extent to which the skills have changed when a curriculum was updated, we compare the skills data of the 88 old curricula to the 88 updated curricula. For each update (a pair of one old and one updated curriculum) we calculate our two dimensions, novelty rate and removal rate.

The novelty rate is a measure for the share of new skills in an updated curriculum. Thus the novelty rate sums up the weights of the skills that appear in the updated curriculum but not in the old one (i.e. these are all skills with weight zero in the old curriculum and positive weight in the updated one). A novelty rate of 100 percent means that, in an updated curriculum, all skills are new skills, whereas a novelty rate of 0% means that there are no skills in the updated curriculum that were not in the old one. In reality the novelty rates lie somewhere in between. A large novelty rate can occur from three types of changes: i) many new skills in an updated curriculum but with small weights, ii) only few new skills but with large weights, or iii) the combination of both, i.e. many new skills with large weights.

In contrast to the novelty rate, the removal rate is a measure for the removal of old skills. This removal rate sums up the weights of the skills that appeared in the old curriculum but not in the updated one. A removal rate of 100 percent would thus mean that all old skills are removed in an updated curriculum. A removal rate of 0 percent would mean that no old skills have been removed. In reality the removal rate lies somewhere in between. Again, a large removal rate can occur because either more skills have been removed, skills with larger weights have been removed or both.

To illustrate how the novelty and removal rates are calculated, we provide a simple hypothetical example of a curriculum update in Table 1. The example takes place in a universe with only four skills. The old curriculum contained three skills (#1, #2, #3) with their respective weights. In the updated curriculum, a skill #4 is added and has a weight of 40%; at the same time the skill #3 has been completely removed and had originally a weight of 30%. This results in a novelty rate of 40% and a removal rate of 30% for this curriculum update.[9]

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[9] Because the reweighting of skills would lead to collinearity of the dimensions, we do not account for it (Skills #1 and #2) in calculating the novelty and removal rates. Moreover, as apprentices need to obtain a skill regardless of the weight it has in a curriculum, we argue that the reweighting is less important than the removal of old skills or introduction of new skills.

Table 1: Illustrative Example of Novelty Rate and Removal Rate in a hypothetical Curriculum Update

	Skill #1	Skill #2	Skill #3	Skill #4	Σ
Old Curriculum	30%	40%	30%	0%	100%
Updated Curriculum	40%	20%	0%	40%	100%
Weight of new skills	**0%**	**0%**	**0%**	**40%**	**40% (Novelty Rate)**
Weight of removed skills	**0%**	**0%**	**30%**	**0%**	**30% (Removal Rate)**

Notes: The first two rows show the skill weights of four hypothetical skills in an old and an updated curriculum. Rows 3 and 4 show the calculation procedure for each of these dimensions.

To illustrate the novelty rate and the removal rate in a real-world example, we examine the update of the VET curriculum for a 'Mechanical Engineer' (Polymechaniker) i.e. a technology-heavy manufacturing occupation. In the real world the curriculum of a mechanical engineer consists of 40 skills. To illustrate how the novelty rate and removal rate are calculated in this update, **Table 2** presents a selection of four important skills from that skill universe: The skill 'Micro/Nanotechnology' did not exist in the old curriculum but was newly introduced in the new curriculum and has a weight of 2.7% in the updated curriculum. At the same time 'Control Technology' was reduced from 8.3% to 7.7%, 'Chemistry' was completely removed from the curriculum, and 'ICT' was increased from 5.1% to 6.7%. If we conduct this procedure for all the skills (not only those represented in the table), we find 10 new skills with a total weight of 14.0%. Thus the updated curriculum for the mechanical engineer has a novelty rate of 14.0%. At the same time 14 skills with a total weight of 17.3% were dropped, i.e. the updated mechanical engineer has a removal rate of 17.3%.

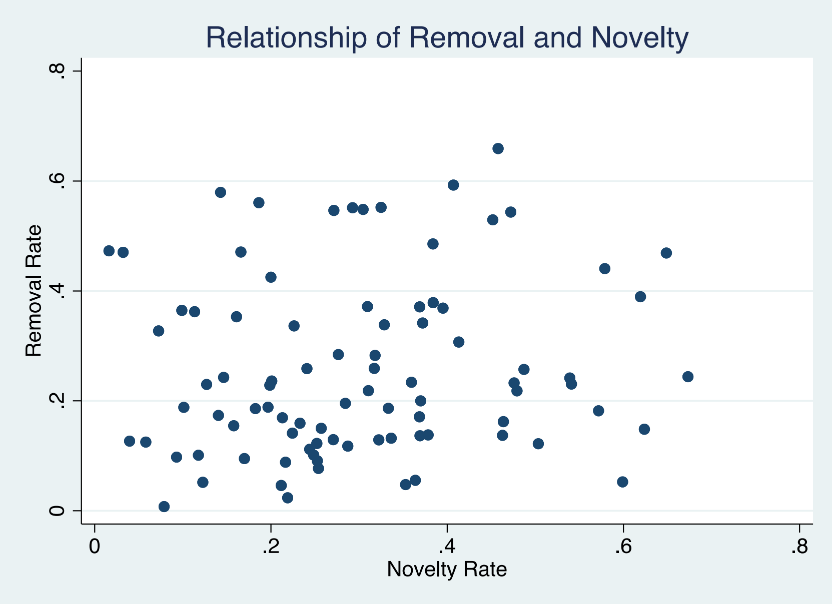
Table 2: Dimensions for the Update of the 'Mechanical Engineer'

Mechanical Engineer	Control Technology	Chemistry	Micro-/Nanotechnology	ICT	Skills 5-40	Σ
Old Curriculum	8.3%	7.8%	0.0%	5.1%	…	100%
Updated Curriculum	7.7%	0.0%	2.7%	6.7%	…	100%
Weight of new skills	**0.0%**	**0.0%**	**2.7%**	**0.0%**	**…**	**14.0% (Novelty Rate)**
Weight of removed skills	**0.0%**	**7.8%**	**0.0%**	**0.0%**	**…**	**17.3% (Removal Rate)**

Notes: – Calculation of dimensions for the update of the 'Mechanical Engineer' in 2009. The table features important skills and considerable changes.

We calculate the novelty rates and the removal rates for all occupational updates in the same way. Figure 2 plots the empirical results for the novelty rate and the removal rate in our sample of 88 curriculum updates and illustrates that some updates focus more on introducing new skills (lower right corner), some updates focus on removing old skills and trimming the curriculum (upper left corner) and some do both at the same time to varying degrees.[10]

Figure 2 - Relation of the Novelty Rate and the Removal Rate



Notes: Authors' calculations based on the skills measurement of old and updated curricula. The correlation coefficient equals 0.1187

3. Labour Market Data and Empirical Strategy

To study the wage effects of these different types of curriculum updates in the next step, we now combine the data on the novelty and removal rates of all the VET curricula with data on labour market outcomes of workers who graduated under the old or the new curricula. For labour market outcomes we use the Social Protection and Labour Market (SESAM) survey, which combines administrative wage data and survey data from the Swiss labour force survey (SLFS) and thus contains rich information for a representative sample of the Swiss population, including information on individuals' education (Federal Statistical Office 2020). After presenting our sample, we explain the specification and present our results.

In our sample we use workers with a VET diploma as their highest education in one of the 88 occupations mentioned earlier. We include one observation per individual in these occupations for the years 2004 to 2020. Based on an individual's year of graduation and the year (t)[11] that an updated curriculum became effective on the labour market (i.e. when the first

[10] More descriptive results can be found in the Appendix.

[11] For example, occupation A introduces its updated curriculum in 2011 and the training duration is three years. Thus, the first individuals who studied the updated curriculum enter the labor market in 2014 which is our reference year (t).

graduates studied under an updated curriculum start working in regular jobs), we define whether the individual was trained in an old or an updated curriculum. We define the group of individuals who studied under the old curriculum as those who graduated before reference year (t). Similarly, we define the group that studied under the updated curriculum as those who graduated in or after reference year (t). We include individuals who graduate within a time window of five years before $(t-5)$ each update and five years after $(t+5)$ each update in our analysis.[12]

For the wage analyses we exclude individuals in the year of their graduation because they were still employed as apprentices for at least part of that year. Finally, given that we analyse wages, we have to drop unemployed individuals because they do not earn wages. After applying all restrictions, our regression sample comprises 7,418 individuals, as summarised in **Table 3**.

For the empirical analysis we link the labour market data with the information on curriculum updates and the novelty and removal rates at the occupational level according to the Swiss Standard Classification of Occupations (CH-ISCO-19). Given its construction, the sample is not completely balanced. For example, individuals who graduated under an old curriculum are systematically older and likely have more work experience because they graduated earlier, than those who studied under an updated curriculum. Moreover, the observations before and after the update are not equally distributed. Therefore, we apply an inverse probability weighting (IPW) approach to correct for these imbalances (e.g. Rosenbaum and Rubin 1983; Wooldridge 2002; Lunceford and Davidian 2004; Cattaneo 2010) that proceeds in two steps in our empirical analysis.

First, we run a logistic regression to calculate the propensity score (*ps*) of an individual belonging to the group of 'updated' individuals. We estimate *ps* as specified in Equation 1:

$$\begin{aligned} ps_i(Update=1) \\ &= \alpha_0 + \alpha_1 Experience_i + \alpha_2 Gender_i + \alpha_3 Occupation_i \\ &+ \alpha_4 Region_i + \alpha_5 EmploymentLevel_i + \varepsilon_i \end{aligned} \tag{1}$$

$Experience$ is the year of observation minus the graduation year for individual (i). $Gender$ takes value 1 if an individual is female, otherwise 0. $Occupation$ denotes the training occupation (one out of the 88 occupations) of individual (i). $Region$ is defined as the location

[12] We do not use more years around the update to keep labour market circumstances sufficiently similar for the graduates that we compare under the old and new curriculum.

(according to the 26 cantons)[13] of the firm where the individual works. $EmploymentLevel$ is the level of employment on a scale of 1% to 100%. **Table 3** reveals, that after the weighting the sample is balanced, i.e. the differences in the sample are strongly reduced. For comparison, see the unweighted sample in **Table B.3** in the Appendix.

Table 3: Summary of Sample (weighted)

	Update = 0		Update = 1			
	mean	sd	mean	sd	diff	t-value
Novelty Rate	0.000	0.000	23.636	11.390		
Removal Rate	0.000	0.000	17.785	11.888		
Experience	3.830	2.923	3.657	2.674	0.173**	(-2.19)
Gender (female=1)	0.479	0.500	0.485	0.500	-0.006	(0.43)
Level of Employment in %	92.485	18.526	92.600	18.129	-0.115	(0.24)
Observations	3886		3532		7418	

Notes: Authors' calculations of the ps-weighted summary statistics for the individuals from the sample. Data based on their learned occupations, our skills measurement and the SESAM/SAKE 2004-2020.

Second, to analyse the effect of a curriculum update, we perform an OLS regression that uses IPW based on ps to account for imbalances in the sample. More specifically, observations of individuals who graduated under an updated curriculum receive the weight $\frac{1}{ps_i}$ and observations of individuals who graduated under an old curriculum receive the weight $\frac{1}{(1-ps_i)}$. The OLS regression is specified in Equation 2:

$$\begin{aligned} log\left(wage_{i(jtfk)}\right) \\ &= \beta_0 + \beta_1 NoveltyRate_{jt} + \beta_2 NoveltyRate^2{}_{jt} \\ &+ \beta_3 RemovalRate_{jt} + \beta_4 RemovalRate^2{}_{jt} + \gamma X_{i(jtk)} + \sigma_i \\ &+ \beta_{10} IndustryVariance_{kt} + \eta Z_f + \mu_{ijtk} \end{aligned} \tag{2}$$

with $wage_{i(jtk)}$ being the wage of individual (i) trained in occupation (j) graduated at time (t) and employed in firm (f) and industry (k).

The dependent variable $log\left(wage_{i(jtfk)}\right)$ is the natural logarithm of an individuals deflated, full-time-equivalent yearly wage. The main explanatory variables are the $novelty\ rate$ and the $removal\ rate$, both of which depend on the occupation and year of graduation. Individuals who were trained under an old curriculum by definition have a novelty

[13] Cantons in Switzerland are regional administrative entities similar to U.S. states.

rate and a removal rate of 0%. Individuals who were trained under an updated curriculum have the respective novelty rate and removal rate of the updated curriculum, which empirically vary between 1.6% and 67.3% (novelty rate) and 0.8% and 65.9% (removal rate). We can interpret the empirical results of our main coefficients as the effect of a certain novelty or removal rate on the wage of an individual, whose curriculum was updated. We also include quadratic terms for $NoveltyRate$ and $RemovalRate$ to allow for non-linear relations. Finally, we use a vector X of individual-level controls (gender, experience, tenure, marital status, foreign nationality) and a vector Z as a set of firm-level controls (canton, firm size) and we include a survey-year fixed effect σ. In our estimations we use standard errors that are clustered on the occupational level because our level of treatment – the novelty rate and the removal rate – are measured on the occupational level.

As the need and the consequences of a curriculum update might depend on industry requirements, and particularly on the technological dynamics in an industry, we include a further control variable $Industry\ Variance$. This indicator captures whether industries are more or less dynamic in their job requirements. To do so, we draw on data from the Swiss Job Market Monitor (SJMM) (Buchmann et al. 2022) and build on previous work of Schultheiss and Backes-Gellner (2022) to measure workplace innovation across industries and time. Specifically, we use information retrieved from the texts of job advertisements of the most innovative (‘frontier’) firms in an industry. These texts can serve as a reliable indicator for the technological dynamics at the workplaces in the respective industry. Increasing and changing skill requirements in these frontier firms in the years before an update indicate increased industry dynamics. We measure this dynamic by using the variance of the number of required skills in the five years preceding a curriculum update.

4. Results

4.1 Effects of Novelty Rate and Removal Rate on Graduates' Wages

Table 4: Main Results

	I	II	III
Novelty Rate	-0.00404***		-0.00565***
	(0.00141)		(0.00212)
Novelty Rate^2	0.00006**		0.00008**
	(0.00003)		(0.00003)
Removal Rate		-0.00296	0.00205
		(0.00208)	(0.00321)
Removal Rate^2		0.00006	-0.00002
		(0.00004)	(0.00006)
Female	-0.07831**	-0.08100***	-0.07745**
	(0.03018)	(0.03045)	(0.03010)
Experience	0.05441***	0.05708***	0.05346***
	(0.00759)	(0.00742)	(0.00737)
Experience^2	-0.00312***	-0.00314***	-0.00305***
	(0.00073)	(0.00073)	(0.00073)
Industry Variance	-0.00044**	-0.00048**	-0.00045**
	(0.00021)	(0.00022)	(0.00022)
Individual Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes
Adj R-squared	0.14031	0.13920	0.14037
Observations	7418	7418	7418

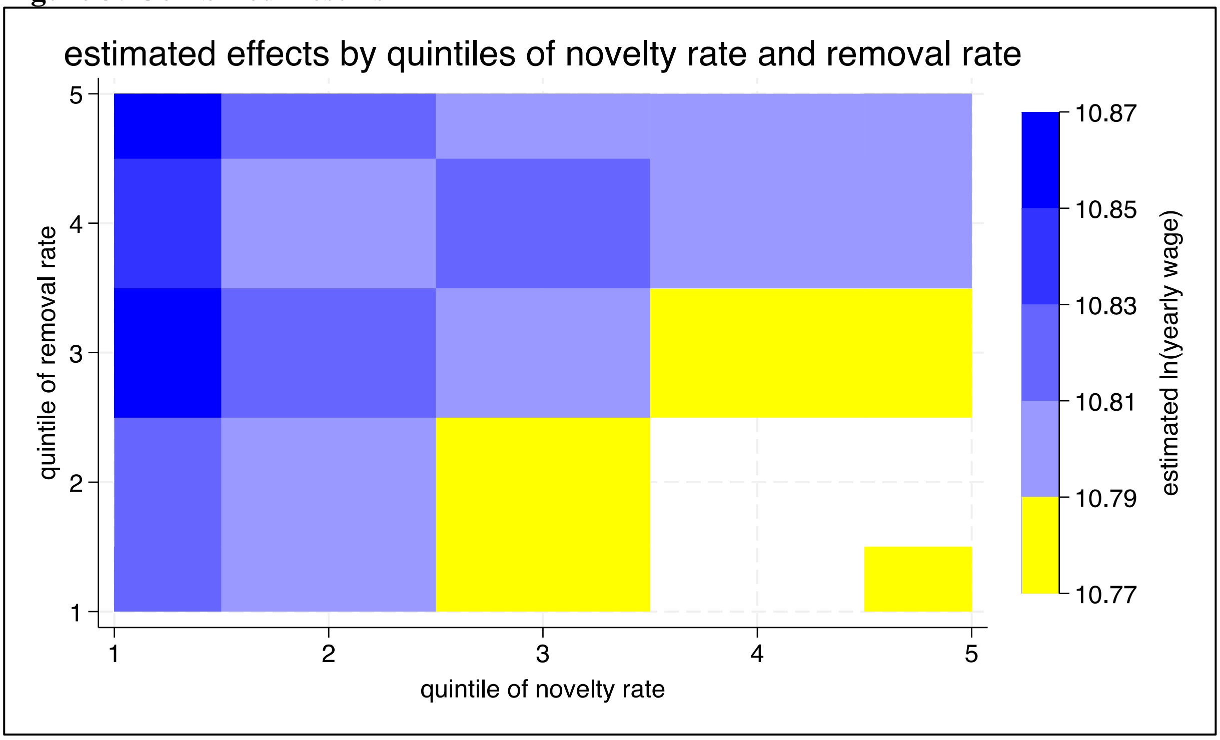
Notes: Data based on our skills measurement and the SESAM/SAKE 2004-2020.
Dependent variable: (ln)yearly wages. Inverse-Probability-Weighted OLS Regressions. Clustered standard errors (on the training occupation) in parentheses. Standard errors in parentheses. Individual controls include tenure, marital status, and foreign nationality. Firm controls include the canton where the firm is located, and firm size.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 now presents the results from the empirical approach presented in section 3. Specification I, which includes only the novelty rate, reveals a u-shaped association with wages. We find that the same pattern in specification II for the removal rate, but the association is much weaker and not statistically significant. However, as each update contains both new and removed skills, our preferred specification is specification III, which includes both dimensions. These results suggest that the relation between the novelty rate and graduates' wages is u-shaped, whereas the relation between the removal rate and graduates' wages is inversely u-shaped, but the latter is statistically insignificant. For a graphical visualization, see **Figure B.3** in the Appendix. Importantly, all four coefficients of interest are jointly significantly different from zero (f-stat: 3.21), indicating that analysing the novelty and removal rate in combination is important. In addition to the main effects, we find that the coefficient for the

$Industry\ Variance$ is significantly negative, which suggests that all else equal graduates in industries that are subject to rapid change, and thus are more disrupted, earn lower wages.

However, we are most interested in the joint effects of a higher or lower novelty rate combined with a higher or lower removal rate. These results are shown in **Figure 3** which splits the sample into quintiles for the novelty rate and the removal rate. The figure reveals several important patterns. First, we see that the estimated wages of graduates from updated curricula are the largest (dark blue areas) when the novelty rate is in the first or second quintile and this is almost independent of the removal rate. Second, we see that for larger novelty rates, the estimated wages are higher only (blue areas) when the removal rate is at the same time sufficiently large; in contrast, combinations of large novelty rates with small removal rates are less favourable (yellow areas). White areas indicate that there are no observations. These two patterns imply that while a curriculum update with a low novelty rate can be combined with any removal rate, an update with a large novelty rate should be combined with a sufficiently large removal rate. This probably also means that updating curricula more frequently with small novelty additions rather than updating them less frequently with large novelty additions seems to be generally a more favourable updating strategy.

Figure 3: Combined Results



Notes: Authors' calculations based on their skills measurement and SESAM 2004 – 2020. The figure plots the estimated marginal effects on ln(yearly wage) for the Removal Rate and the Novelty Rate together for different quintiles in the distribution of updates. The quintiles of novelty rate (N) are (1) N ∈ [1.62%, 11.77%], (2) N ∈ [12.27%, 19.67%), (3) N ∈ [19.88%, 25.39%), (4) N ∈ [25.71%, 31.73%), and (5) N ∈ [31.82%, 67.33%]. The quintiles of removal rate (R) are (1) R ∈ [0.77%, 7.70%), (2) R ∈ [8.83%, 10.10%), (3) R ∈ [10.13%, 17.35%), (4) R ∈ [18.19%, 23.60%), and (5) R ∈ [24.15%, 65.91%]. The white space indicates cells with no observations.

4.2 Additional Analysis and Skill Categorisation

In this part we provide a further analysis that investigates the actual skills that are added or removed in updated curricula and illustrates the concrete trade-offs that curriculum designers faced in the sample period from 2005-2015. We investigate which skills have actually increased or decreased in weight as a result of all the curriculum updates in our sample from 2005-2015. For this analysis, we group the skills into larger skill categories. We apply a data-driven approach using the curriculum texts of the training sample from the NLP method described section 3.2 and Appendix A. We proceed in the following three steps: First, as each skill is represented with a multidimensional vector, we calculate the cosine similarity between the skills. Second, we take the smallest skill according to its weight across all curricula under analysis (176) and merge it with the most similar skill. Third, we calculate the vectors for the new (merged) skill. We repeat these three steps multiple times. We use the resulting 25 skill categories to show both important changes along the 88 curriculum updates and the association of these categories with wages.

We use the 25 skill categories to get a better overview of what types of skills have been changed the most and in which direction (removed or added). Results are reported in **Table 5**. We find that the largest group of novel skills that are added across all curricula are ‘generic skills’ that can be used in any type of occupation and ‘focused technological skills’ that match the technological changes during the respective time period. Examples of such ‘generic skills’ are social skills, organizational skills, or quality control and safety skills; examples of ‘focused technological skills’ are specific IT skills or control and precision technology skills like CNC, ‘control technology’ or ‘automatization’. On the other hand we find that the largest group of obsolescent skills that are removed with a positive labour market outcome are largely either ‘narrow manual skills’ or ‘general education foundation skills’. Examples of the former are ‘model making’ and ‘furniture making’; examples of the latter are ‘chemistry’ or ‘physics’.

Table 5: Increase and Decrease of Weights for the 25 Skill Categories

Skill Category	Mean	Std. Dev.	Min	Max
Safety & Quality	3.000	6.523	-12.219	25.093
Organizational Skills	1.709	4.629	-10.904	13.139
Social Skills	1.378	6.429	-17.245	23.004
Logistics	1.227	5.041	-14.263	36.624
Hygiene Cleaning	1.112	3.371	-5.755	21.834
Documentation	1.043	3.322	-8.830	15.929
Manufacturing	.802	8.233	-35.001	23.567
Environment Protection	.649	3.703	-11.773	12.547
Medicine	.517	3.498	-5.602	26.460
Maintaining	.482	4.085	-12.861	13.687
Machines & Motors	.376	4.089	-7.134	25.401
Control & Precision Techn.	.357	3.185	-11.299	7.946
IT	.254	4.986	-11.200	31.197
Surfaces	.051	3.974	-16.626	15.873
Printing	-.214	2.155	-8.333	6.667
Installations	-.324	4.838	-26.001	19.253
Business	-.527	3.570	-14.669	8.212
Electrotechnics	-.604	3.129	-11.860	10.263
Food	-.619	4.756	-18.990	28.813
Biology	-1.152	6.583	-28.825	29.605
Mathematics	-1.262	2.889	-13.978	4.942
Chemistry	-1.948	3.649	-18.667	4.811
Materials Science	-2.077	4.276	-23.478	5.285
Physics	-2.095	4.083	-22.153	4.982
Manual Skills	-2.134	7.204	-30.386	11.835

Notes: Authors' calculations based on their skills measurement. Number of observations: 88. (The unit of observation is the 88 updates in the sample). Table shows the changes of each of the skill categories on the update level. The number of observations is 88. Reading example: Skills included in the skill category 'Safety & Quality' have on average a 3.00 percentage point higher weight in updated curricula compared to old curricula.

We then analyse whether these specific types of changes are associated with changes in graduates' wages. To do so, we replace the variables 'novelty rate' and 'removal rate' in equation 2 with variables measuring the 'differences in skill categories' from **Table 5**. Thus we capture the effect of receiving more or less of a given skill category after a curriculum update on the wages of graduates from the updated curriculum in comparison to graduates from the old curriculum. **Table 6** provides the results for these estimations. It reveals that most of the skill categories that increased their weight in the observed time period were on average positively related to wages. At the same time, also skill categories that were actually removed in that time period (i.e. the 'general education foundation skills') are on average positively related to wages. This indicates that it is important for curriculum designers to indeed think carefully about the trade-off between adding which new skills and removing which old skills.

Table 6: Association of Skill Categories with Wages

Skill Categories	Coefficient	Standard Error
Safety & Quality	0.00663*	0.00337
Organisational Skills	-0.00293	0.00387
Social Skills	0.00513*	0.00300
Logistics	0.00611***	0.00226
Hygiene & Cleaning	-0.00266	0.00491
Documentation	0.00896	0.00652
Manufacturing	0.00120	0.00228
Environment Protection	0.00815	0.00632
Medicine	-0.00058	0.00379
Maintaining	-0.00504	0.00438
Machines & Motors	omitted	.
Control & Precision Technologies	-0.01529***	0.00509
IT	0.00636	0.00429
Surfaces	0.00175	0.00417
Printing	0.02308**	0.00976
Installations	0.01166***	0.00269
Business	0.00020	0.00380
Electrotechnics	-0.00337	0.00988
Food	0.00428	0.00441
Biology	0.00072	0.00264
Mathematics	0.01216	0.00880
Chemistry	-0.00463	0.00486
Materials Science	0.00340	0.00509
Physics	0.00894*	0.00509
Manual Skills	-0.00171	0.00231
Female	-0.06661**	0.03226
Experience	0.05957***	0.00748
Experience^2	-0.00315***	0.00072
Industry Variance	-0.00046**	0.00022
Individual Controls	Yes	
Firm Controls	Yes	
Year Controls	Yes	
Adj R-squared	0.14388	
Observations	7418	

Notes: Data based on our skills measurement and the SESAM/SAKE 2004-2020.
Dependent variable: ln(yearly wages). Inverse-Probability-Weighted OLS Regressions. Clustered standard errors (on the training occupation) in parentheses. Standard errors in parentheses. Individual controls include tenure, marital status, and foreign nationality. Firm controls include the canton where the firm is located, and firm size. Interpretation example: A one percentage point increase in the weight of skills in the category 'Safety & Quality' is associated with a increase in ln(yearly wages) by 0.66%.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusions

In this paper, we examine the nature of curriculum updates and its relation to wages of graduates from updated curricula. In contrast to previous work, we do not focus on particular skills that have been added to updated curricula (such as CNC or CAD) but we look at the share of any new skill that has been added to a curriculum (no matter what the skill itself may be) and, likewise, the share of any old skill that has been removed from a curriculum. We use Swiss VET curricula to define and measure these two dimensions of curriculum updates and call them the 'novelty rate' and the 'removal rate'. Our descriptive results show that curriculum updates are heterogenous with respect to these two dimensions. Some add few new skills but may heavily remove old skills, some may add many new skills but may remove hardly any old skills and all combinations thereof.

We use these data to first study the effect that adding smaller or larger amounts of new skills to an updated occupational curriculum (i.e. smaller or higher novelty rates) has on labour market outcomes of graduates that were educated under an updated curriculum. Second, we examine the effect of removing smaller or larger amounts of old skills from an updated occupational curriculum (i.e. smaller or larger removal rates) has on their labour market outcomes. Third, we analyse how different combinations of high or low novelty rates combined with high or low removal rates affect labour market outcomes.

In our econometric analyses we find evidence for non-linear relations: the relation between the novelty rate with wages is u-shaped whereas the relation of the removal rate with wages is inversely u-shaped. Most important are the combined results of adding and removing skills. While adding lots of new skills without removing old ones is not beneficial, removing old skills with all kinds of curriculum updates is. In other words, for a curriculum update that adds any amount of new skills it is crucial to always remove a sufficient number and weight of the old skills to be able to gain the best results on labour market outcomes of graduates. If with the addition of new skills there are too few old skills that are removed, an update risks to inflate the curriculum content and make it less effective in all dimensions. However, regardless of the level of the novelty rate, removing old skills is always a reasonable strategy.

In an additional analysis we investigate the actual skills that are added or removed in updated curricula to better illustrate the concrete skill trade-offs that curriculum designers were faced with in the sample period from 2005-2015. We investigate which skills have actually increased or decreased in weight as a result of all the curriculum updates in our sample period. We find that the largest group of novel skills that are added across all curricula are 'generic skills’ (e.g. social skills, organizational skills, or quality control and safety skills) that can be used in any type of occupation and ‘focused technological skills’ (e.g. IT skills or control and precision technology skills such as CNC, control technology or automatization) that match the technological changes during the respective time period. On the other hand, we find that the largest group of skills that are removed are largely either ‘narrow manual skills’ (e.g. model making and furniture making) or ‘general education foundation skills’ (e.g. chemistry or physics). This shows what the choices and the trade-offs were that curriculum designers faced with in the respective period.

Our paper contributes to the economics literature by showing that the nature of curriculum updates – i.e. the combination of adding new skills and removing old skills – is related to labour market outcomes. We find that removing outdated skills is crucial because, given the fixed time of VET programmes, the time spent on acquiring old skills may be used more efficiently for learning new and often (but not always) more important skills. Adding too many new skills at once could interrupt established learning processes or throw previously well-rounded skill bundles out of balance.

Methodologically, our study uses a novel approach to capturing the nature of a curriculum update by introducing, defining, and applying two dimensions of curriculum updates – the novelty rate and the removal rate. This approach allows to capture changes in any type of skill and to see how the changes as a whole affect labour market outcomes. Our approach is transferable to other curriculum updates, especially those in which curricula are systematically and extensively revised.

Our findings have important implications for policymakers and the many types of stakeholders involved in updating curricula, especially in economies that are or want to come closer to the innovation frontier. Striking the right balance between adding new skills to promote innovation and removing old skills to avoid overloading the curricula is a crucial target for curriculum designers. The challenge lies in determining the optimal amount of new skills while also removing outdated skills. Given that an endless addition of new skills is simply not feasible, the key is to identify a viable combination of adding new skills, reweighting existing ones and removing those that are less important. Thus, the addition of new skills should be complemented by the removal of old skills so that instructors have enough time to teach skills well and students have enough time to acquire them.

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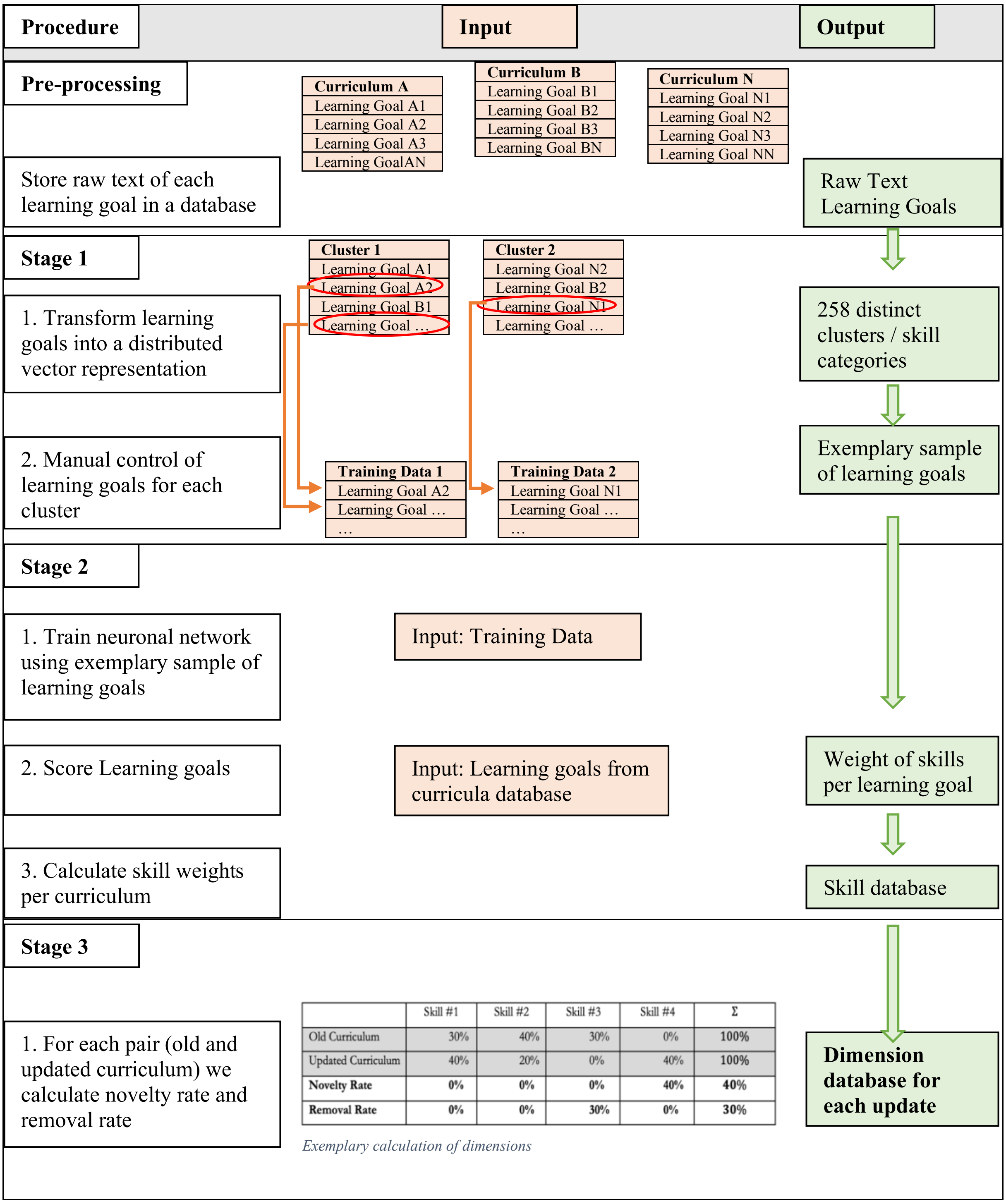
Appendix A: Skill extraction procedure and dimensions calculation

To identify the different single skills mentioned in all the curriculum texts, we use NLP methods following Eggenberger and Backes-Gellner (2023). For all the details see (Eggenberger and Backes-Gellner (2022, 2023). We first manually extract the raw text of each learning goal (i.e. a description of a required skill) from the curricula and store them in a database. Then, we apply a machine learning method consisting of a two-stage procedure. In the first stage (see Figure A1), we build skills categories by transforming the learning goals into a distributed vector representation. These vector representations, a natural language processing (NLP) method, use external text corpora to transform the raw text into vectors that encode semantic meaning. Specifically, we use a sentence transformer model based on BERT (Devlin et al. 2023). Repeated clustering by an unsupervised algorithm leads to 258 distinct clusters which we then use as interpretable skill categories. After that, we draw a random selection of learning goals attributed to each category. To improve precision in second stage, we manually control the assignment of the learning goals to each category and select an exemplary sample of learning goals which we then use as training data in the second stage.

In the second stage, we use this exemplary sample as training data in a neural network classification model. During training, the network learns to detect a large number of patterns that can occur in any input text. After training, the network will then search for patterns in the given input (i.e. the raw text learning goals) and assign the input texts to the 258 skill categories generated in stage one. This allows us to score all our learning goals with probabilities to belong to each of the categories. A learning goal can be assigned to one or more skill categories. In the last step, we transform this data into a dataset with detailed information on the categories and weight of each skill in a curriculum. To do so, we weight the assigned skill probabilities of each learning goal with the inverse of the total number of learning goals in a curriculum. We assign each learning goal to all categories where it has a probability of more than 25%. Thus, a learning goal can be assigned to a maximum of three categories in case it featured multiple skills.

We then introduce a third stage where we use this skill database to calculate our two dimensions novelty rate and removal rate. This stage is explained in detail in section 2.3 and the result is a database with updates and its dimensions.

Figure A1: Skill Extraction Procedure and Dimensions Calculation



	Skill #1	Skill #2	Skill #3	Skill #4	Σ
Old Curriculum	30%	40%	30%	0%	100%
Updated Curriculum	40%	20%	0%	40%	100%
Novelty Rate	0%	0%	0%	40%	40%
Removal Rate	0%	0%	30%	0%	30%

Exemplary calculation of dimensions

Notes: Based on Eggenberger and Backes-Gellner (2022)

Appendix B: Additional Figures and Tables

Table B.1: Full List of Updates and Dimensions

Occupation (New Occupational Title)	Occupation (German)	Novelty Rate	Removal Rate	Year Update
Building Constructor	Polybauer EFZ	67.33%	24.40%	2008
Textile Worker	Textilpflegerin EFZ	64.87%	46.90%	2008
Surveyor	Geomatiker EFZ	62.38%	14.84%	2010
Advertising Designer	Gestalter Werbetechnik EFZ	61.94%	38.95%	2006
Roofer	Polybauer EFZ, Dachdecken	59.91%	5.25%	2008
Laboratory Assistant	Laborant EFZ - Chemie	57.89%	44.06%	2008
Road Builder	Strassenbauer EFZ	57.18%	18.19%	2008
Print Finisher	Printmedienverarbeiter EFZ	54.10%	23.05%	2006
Multimedia Electronics Technician	Multimediaelektroniker EFZ	53.92%	24.15%	2014
Bicycle Mechanic	Fahrradmechaniker EFZ	50.34%	12.20%	2012
Bricklayer	Maurer EFZ	48.72%	25.71%	2011
Barrel Maker	Küfer EFZ	47.92%	21.82%	2009
Carpenter	Zimmermann EFZ	47.60%	23.25%	2014
Refrigeration System Technician	Kältesystem-Monteur EFZ	47.22%	54.35%	2012
Plant and Equipment Manufacturer	Anlagen- und Apparatebauer EFZ	46.38%	16.21%	2013
Gardener	Gärtner EFZ	46.28%	13.72%	2012
Fabric Designer	Gewebegestalter EFZ	45.78%	65.91%	2011
Stove Builder	Ofenbauer	45.18%	52.94%	2011
Textile Technologist	Textiltechnologin EFZ	41.32%	30.70%	2007
Leather and Textile Worker	Fachmann Leder und Textil EFZ	40.71%	59.27%	2012
Cabinetmaker	Schreiner EFZ - Möbel Innenausbau	39.53%	36.88%	2014
Optician	Augenoptiker EFZ	38.41%	37.87%	2011
Blacksmith	Hufschmied EFZ	38.39%	48.55%	2009
Stone Sculpter	Steinbildhauer EFZ	37.84%	13.80%	2010
Floor Layer	Boden-Parkettleger EFZ	37.23%	34.17%	2012
Electrical Installation Designer	Elektroplaner EFZ	37.00%	19.99%	2007
Tinsmith	Spengler EFZ	36.92%	13.65%	2008
Clothing Designer	Bekleidungsgestalter EFZ	36.88%	37.11%	2014
Draftsman	Zeichner EFZ	36.68%	17.10%	2010
Healthcare Worker	Fachmann Gesundheit EFZ	36.39%	5.54%	2009
Information and Documentation Expert	Fachmann Information und Dokumentation EFZ	35.95%	23.38%	2009
Plastics Technologist	Kunststofftechnologe EFZ	35.28%	4.76%	2008
Powerline Technician	Netzelektriker EFZ	33.65%	13.21%	2014
Butcher	Fleischfachmann EFZ	33.33%	18.64%	2008
Panel Beater	Carrossier Spenglerei EFZ	32.87%	33.83%	2006
Industrial Upholsterer	Industriepolsterer EFZ	32.50%	55.21%	2011
Heating System Installer	Heizungsinstallateur EFZ	32.24%	12.90%	2008
Car Body Painter	Carrossier Lackiererei EFZ	31.82%	28.27%	2006
Specialist in Professional Kitchen	Koch EFZ	31.73%	25.90%	2010
Electrician	Elektroinstallateur EFZ	31.06%	21.85%	2007
Photography Expert	Fotofachmann EFZ	30.96%	37.16%	2005
Painter	Maler EFZ	30.46%	54.83%	2015
Truck Driver	Strassentransportfachmann EFZ	29.26%	55.14%	2013

Forester	Forstwart EFZ	28.73%	11.76%	2007
Micromechanical Engineer	Mikromechaniker EFZ	28.45%	19.54%	2013
Engraver	Graveur EFZ	27.65%	28.42%	2011
Baker-Confectioner	Bäcker-Konditor-Confiseur EFZ	27.14%	54.65%	2011
Stonemason	Steinmetz EFZ	27.08%	12.93%	2010
Building Services Technician	Gebäudetechnikplaner EFZ	25.71%	15.00%	2010
Commercial Employee	Kaufmann EFZ	25.39%	7.70%	2012
Mediamatics Technician	Mediamatiker EFZ	25.27%	9.09%	2011
Beautician	Kosmetiker EFZ	25.21%	12.24%	2007
Bookseller	Buchhändler EFZ	24.85%	10.13%	2009
Agricultural Machinery Mechanic	Landmaschinenmechaniker EFZ	24.40%	11.18%	2007
Metal Worker	Metallbauer EFZ	24.08%	25.86%	2007
Ventilation and Air-Conditioning Technician	Lüftungsanlagenbauer EFZ	23.30%	15.93%	2008
Dental Technician	Zahntechniker EFZ	22.62%	33.63%	2008
Premedia Specialist	Polygraf EFZ	22.44%	14.13%	2007
Building and Grounds Custodian	Fachmann Betriebsunterhalt EFZ	21.90%	2.36%	2015
Graphic Designer	Grafiker EFZ	21.65%	8.83%	2010
Hairdresser	Coiffeur EFZ	21.30%	16.92%	2006
Chemical and Pharmaceutical Technologist	Chemie- und Pharmatechnologe EFZ	21.17%	4.60%	2006
Hospitality Services Professional	Fachmann Hauswirtschaft EFZ	20.09%	23.61%	2005
Food Technologist	Lebensmitteltechnologe EFZ	20.00%	42.51%	2013
Automotive Technician	Automobil-Mechatroniker EFZ	19.88%	22.84%	2007
Sanitation Technician	Sanitärinstallateur	19.67%	18.84%	2008
Specialist in Restaurant Service	Restaurationsfachmann EFZ	18.63%	56.06%	2005
Florist	Florist EFZ	18.24%	18.59%	2008
Logistician	Logistikerin EFZ	16.99%	9.50%	2010
IT Specialist	Informatiker EFZ	16.59%	47.08%	2005
Goldsmith	Goldschmied EFZ	16.10%	35.30%	2010
Automatician	Automatiker EFZ	15.78%	15.46%	2009
Printing Technologist	Drucktechnologe EFZ	14.63%	24.27%	2009
Metal Casting Moulder	Gussformer EFZ	14.29%	57.94%	2013
Mechanical Engineer	Polymechaniker EFZ	14.04%	17.35%	2009
Veterinary Nurse	Tiermedizinischer Praxisassistent EFZ	12.70%	22.99%	2008
Dental Assistant	Dentalassistent EFZ	12.27%	5.17%	2010
Retail Clerk	Detailhandelsfachmann EFZ	11.77%	10.10%	2005
Medical Assistant	Medizinischer Praxisassistent EFZ	11.34%	36.22%	2010
Design Engineer	Konstrukteur EFZ	10.11%	18.82%	2009
Pharmaceutical Assistant	Pharmaassistent EFZ	9.89%	36.46%	2007
Animal Caretaker	Tierpfleger EFZ	9.29%	9.76%	2010
Podiatrist Assistant	Podologe EFZ	7.88%	0.76%	2013
Electroplater	Oberflächenbeschichter EFZ	7.25%	32.72%	2010
Electronics Engineer	Elektroniker EFZ	5.80%	12.50%	2009
Social Care Worker	Fachmann Betreuung EFZ	3.96%	12.67%	2011
Dairy Technician	Milchtechnologe EFZ	3.23%	47.02%	2012
Recyclist	Recyclist EFZ	1.62%	47.30%	2011

Notes: Authors' calculations of the two dimensions for each update. Sorted by the novelty rate.

Table B.2: Descriptive Statistics of Novelty Rate and Removal Rate across all Curriculum Updates

Variables	Obs	Mean	SD	Min	Max
Novelty Rate	88	.300	.155	.016	.673
Removal Rate	88	.257	.161	.008	.659

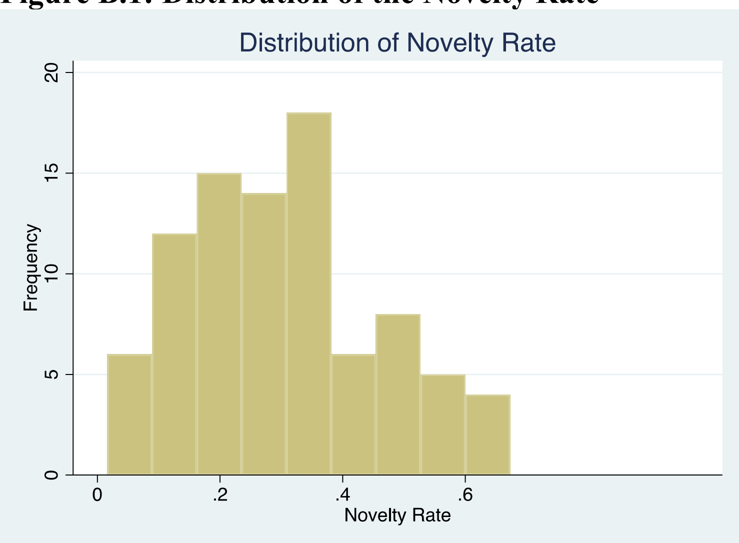
Notes: Summary Statistics of the two dimensions. Authors' calculations. The number of observations corresponds to the number of updates in the sample.

Table B.3: Summary of Sample (unweighted)

	Update = 0		Update = 1			
	mean	sd	mean	sd	diff	t-value
Novelty Rate	0.000	0.000	23.001	11.405		
Removal Rate	0.000	0.000	17.437	11.658		
Experience	4.823	3.143	3.033	2.265	1.790***	(27.902)
Gender (female=1)	0.454	0.498	0.509	0.500	-0.055***	(-4.777)
Level of Employment in %	91.924	19.227	92.803	17.770	-0.878*	(-2.037)
Observations	3886		3532		7418	

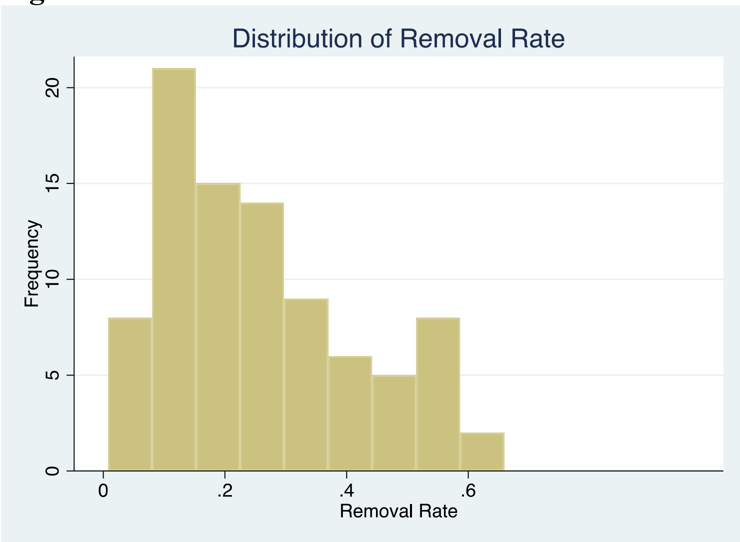
Notes: Authors' calculations of the unweighted summary statistics for the individuals from the sample. Data based on their learned occupations, our skills measurement and the SESAM/SAKE 2004-2020.

Figure B.1: Distribution of the Novelty Rate



Notes: Authors' calculations. Frequency reflects number of updates in given bin.

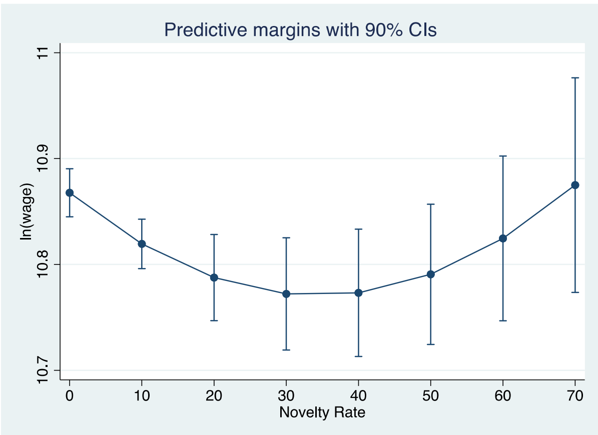
Figure B.2: Distribution of the Removal Rate



Notes: Authors' calculations. Frequency reflects number of updates in given bin.

Figure B.3: Estimated wages by novelty rate and removal rate

Panel B.3a: Estimated wages by novelty rate



Panel B.3b: Estimated wages by removal rate