

# Skills, Employer-Provided Training, and the COVID-19 Pandemic

**Report****Author(s):**

Caves, Katherine Marie ; McDonald, Patrick 

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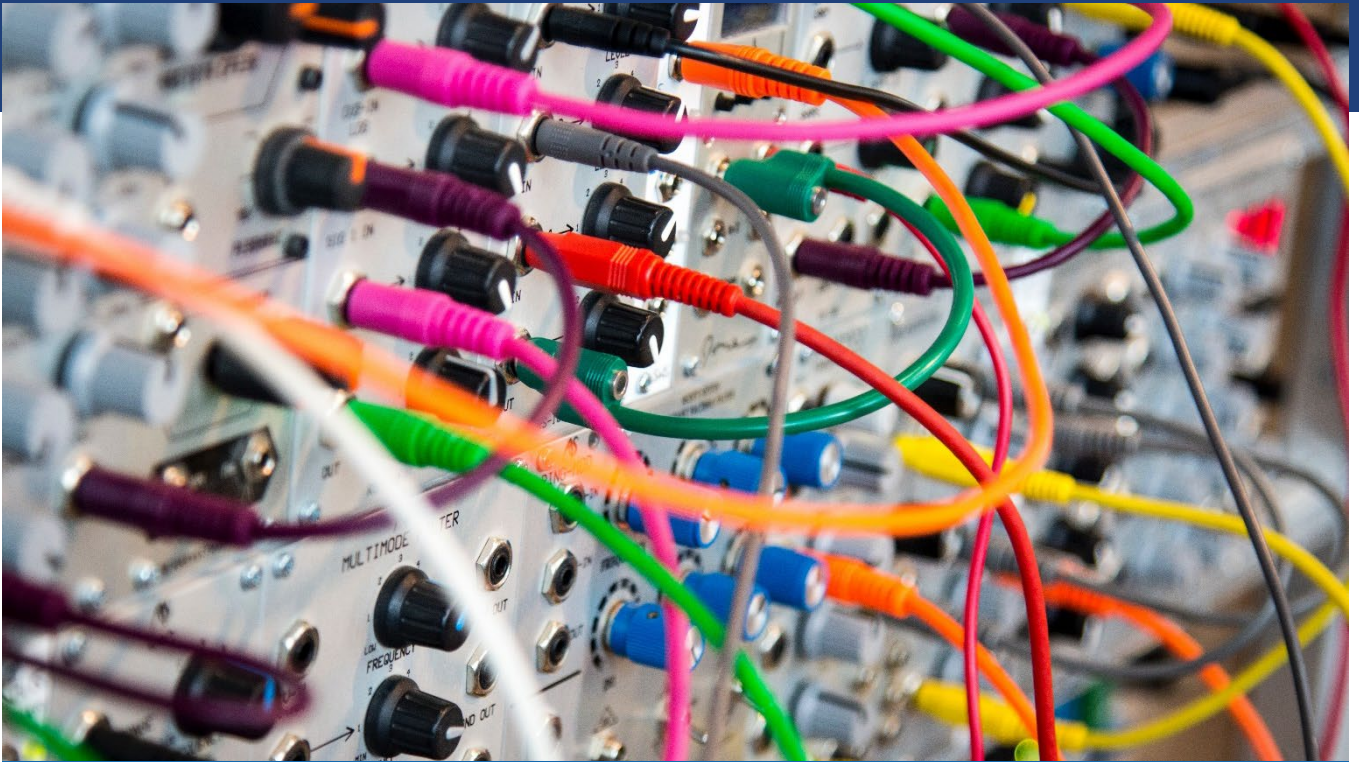
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# Skills, Employer-Provided Training, and the COVID-19 Pandemic

**Authors:**

Katherine Caves  
Patrick McDonald

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Report prepared by the Chair of Education Systems team at ETH Zurich in Zurich, Switzerland (<http://www.ces.ethz.ch/>) in cooperation with the Center on Education and Labor at New America (<https://www.newamerica.org/center-education-labor/>)

**ETH** zürich



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# Abstract

This report analyzes the state of work-based training among organizations who are members of the Partnership to Advance Youth Apprenticeship (PAYA) and CareerWise USA networks. A non-representative sample of 682 employers responded to a survey between April and June 2021. The survey contained sections on reasons for training, quality of training programs, and the impact of the COVID-19 pandemic on in-work training. Using a combination of OLS linear regression models and state-level random-intercept models, this report takes each of these topics in turn and analyzes key outcomes and their variation by employer characteristics such as sector, industry, and share of workers by race/ethnicity and gender.

Overall, the results indicate a variety of reasons for training, both economic and social, generally high levels of quality measures across programs and employer types, and only limited impacts of the pandemic on training. Apprenticeships and professional development programs offer high levels of positive outcomes for participants in terms of recognized internal or external certification, and also rate highly on quality indicators such as wages, dedicated trainers and curricula, and quality control processes. Conversely, on-the-job training and internships offer fewer credentials and rate lower on quality indicators. These programs were also the most likely to be disrupted by the pandemic. The impacts of COVID were also less likely to be felt by programs targeted at youth – generally apprenticeships – but programs that were more diverse than the employer overall felt stronger negative impacts of the pandemic. Expectations of future effects of COVID-19 by employers were shown to be as important as the impact to date, and higher levels of COVID stringency at the state level did not in all cases translate to more program interruption, perhaps because states that imposed stricter measures also provided more economic support.

In short, while the overall state of in-work training within the employers surveyed is good, there remains some variation based on the kind of program and its target demographic. That more diverse programs seem somewhat less strong holds implications for questions of equity of access, and workplace training as a means of redressing educational and economic inequities. However, it is important to note that selection into the sample may have implications for broader interpretations of the results. The results hold for the sample population, but are not representative of the US training landscape overall. Moreover, the timing of the survey towards the end of many of the stricter COVID-19 control measures may mean the survey results only capture employers who survived the crisis. The presumably negative implications of company closure on access to in-work training are therefore missing from the analysis.

# 1 Introduction

The COVID-19 pandemic disrupted every segment of society. The American labor market and training landscape were not spared. Unemployment spiked at the onset of the pandemic, peaking at 14.8% in April of 2020<sup>1</sup>. Workers flooded onto the labor market, but by 2021 employers began reporting a labor shortage<sup>2</sup>. At the same time, the pandemic disrupted day-to-day operations across industries with workers moving to remote work, adding personal protective equipment, and following new regulations around social distancing. Taken together, these phenomena could have a major impact on the landscape of skills and training in the United States.

Employers' struggle to fill positions despite numerous un- and underemployed workers looking for positions is an ongoing issue in many states. In Colorado for example, the problem was referred to in 2018 as the "Colorado Paradox" and employers expressed worry they would not be able to fill the positions created by rapid economic growth because they could not find the skills they need<sup>3</sup>. The implications for individuals are not evenly distributed—California's economy also boomed in the 2010s, but its youth struggled<sup>4</sup>. This mismatch in skills supply and demand is not just a product of a growing economy. Pre-pandemic research had identified mismatches around certain occupations and types of jobs<sup>5</sup>, but it is not clear whether and how these mismatches have changed due to the COVID-19 pandemic. Early evidence suggests that a large number of employees will require re- or up-skilling to respond to structural changes in the labor market<sup>6</sup>.

Employer-provided training is often the best way for individuals to get employable skills and for employers to get skilled workers. Employers have comparative advantages for training certain types of skills<sup>7</sup> and have the information and resources to identify and convey the right skills<sup>8</sup>. Employers provide various forms of training, including on-the-job training, apprenticeships, professional development, and internships. There is a great deal of variation even within one type of program—for example apprenticeship includes Registered Apprenticeships, youth apprenticeships for high school students<sup>9</sup>, and potentially even employers' own models. These differences in training programs might be very important for their resilience to a major economic shock like the COVID-19 pandemic<sup>10</sup>.

<sup>1</sup> Federation of American Scientists. (2021). Unemployment Rates During the COVID-19 Pandemic. <https://fas.org/sgp/crs/misc/R46554.pdf>

<sup>2</sup> The Economist (May 1<sup>st</sup> 2021). Why are American workers becoming harder to find? <https://www.economist.com/finance-and-economics/2021/04/29/why-are-american-workers-becoming-harder-to-find>

<sup>3</sup> Johnston, M. (August 17 2018). Colorado must invest in education if it is to remain competitive. The Denver Post. <https://www.denverpost.com/2018/08/17/colorado-report-card/>

<sup>4</sup> Koller, V. (2018). Closing the gap: The future of apprenticeship in California. Social Policy Research Associates. <https://files.eric.ed.gov/fulltext/ED594003.pdf>

<sup>5</sup> Symonds, W., Schwartz, R., & Ferguson, R. (2011). Pathways to prosperity: Meeting the challenge of preparing young Americans for the 21<sup>st</sup> century. Harvard University Graduate School of Education. [https://www.gse.harvard.edu/sites/default/files/documents/Pathways\\_to\\_Prosperty\\_Feb2011-1.pdf](https://www.gse.harvard.edu/sites/default/files/documents/Pathways_to_Prosperty_Feb2011-1.pdf)

<sup>6</sup> Belachew, T., & Surkin, R. This is the new skills gap for young people in the age of COVID-19. World Economic Forum. <https://www.weforum.org/agenda/2020/10/youth-employment-skills-gap-covid-19/>

<sup>7</sup> Bolli, T., & Renold, U. (2017). Comparative advantages of school and workplace acquisition: Empirical evidence from a survey among professional tertiary education and training students in Switzerland. Evidence-based HRM, 5(1), 6—29. <https://www.emerald.com/insight/content/doi/10.1108/EBHRM-05-2015-0020/full/html>

<sup>8</sup> Bolli, T., Caves, K., Renold, U., & Buergi, J. (2018). Beyond employer engagement: Measuring education-employment linkage in vocational education and training programmes. Journal of Vocational Education and Training, 70(4), 524—563. [https://www.tandfonline.com/doi/pdf/10.1080/13636820.2018.1451911?casa\\_token=KYDPb1nZ6GoAAAAA:ESrf80v2sUwsqKWDjkhk2e\\_rnCtAjVzFayAqXwby\\_twqV083PurBIRBTN4p7zZZIFnk1IVc\\_59aE6A](https://www.tandfonline.com/doi/pdf/10.1080/13636820.2018.1451911?casa_token=KYDPb1nZ6GoAAAAA:ESrf80v2sUwsqKWDjkhk2e_rnCtAjVzFayAqXwby_twqV083PurBIRBTN4p7zZZIFnk1IVc_59aE6A)

<sup>9</sup> Parton, B. (2017). Youth Apprenticeship in America Today: Connecting High School Students to Apprenticeship. New America. <https://www.newamerica.org/education-policy/policy-papers/youth-apprenticeship-america-today/>

<sup>10</sup> Lüthi, S., & Wolter, S. (2020). Are apprenticeships business cycle proof? Swiss Journal of Economics and Statistics, 156(3). <https://link.springer.com/article/10.1186/s41937-019-0047-1>

## 2 Method

We collected data through an online survey of training companies across the United States. The survey is not representative, instead targeting training employers through the networks of the Partnership to Advance Youth Apprenticeship (PAYA) and CareerWise USA. Data collection ran from April-June, 2021.

### 2.1 Sample and Data

The survey was disseminated to employers within the two networks via email and social media channels, though the latter represent very few responses. 5,809 opened the link. However, analysis required that they be at least half complete, so we used 682 responses. We cannot calculate the response rate precisely due to the different dissemination methods, but approximately 12% of survey clicks provided a complete enough survey to be included in the analysis. The sample focuses on training employers—not all employers—but is still not representative.

We use responses from 38 states and Washington DC, shown in Table 1. Most responses come from Midwestern states (407), followed by the South (172) with the West (72) and Northeast (27) far behind. This is mainly driven by the extremely high response rate in Wisconsin. Because the sample is not representative, we emphasize analytical results rather than descriptive results and check for state-level clustering of standard errors. The analytical results show what employer, training, and other characteristics change our outcomes, but should still be interpreted with caution.

Table 1: Responses by state

State	Respondents	State	Respondents
Alabama	4	Montana	6
Alaska	1	Nebraska	-
Arizona	3	Nevada	-
Arkansas	-	New Hampshire	2
California	38	New Jersey	1
Colorado	7	New Mexico	-
Connecticut	-	New York	15
Delaware	1	North Carolina	86
Florida	1	North Dakota	-
Georgia	2	Ohio	1
Hawaii	-	Oklahoma	1
Idaho	-	Oregon	4
Illinois	30	Pennsylvania	3
Indiana	53	Rhode Island	1
Iowa	1	South Carolina	3
Kansas	1	South Dakota	1
Kentucky	2	Tennessee	-
Louisiana	-	Texas	40
Maine	1	Utah	-
Maryland	8	Vermont	-
Massachusetts	3	Virginia	5
Michigan	17	Washington	12
Minnesota	4	Washington DC	17
Mississippi	2	West Virginia	1
Missouri	11	Wisconsin	289
		Wyoming	-



## 2.1.1 Employer characteristics

We differentiate among employers by specifically sector and size. 27.8% of employers in the sample come from the public sector, 55.7% from the private sector, and 16.5% from the nonprofit sector. We include three categories of size. Small employers have 1-49 full-time-equivalent employees (FTE), medium employers have 50-249 FTE, and large employers have more than 250 FTE. Our sample includes 51.1% small employers, 26.3% medium employers, and 22.6% large employers.

In addition, we also include employers' racial and gender diversity and the employer's industry. Table 2 shows how many respondents fall into each industry category. Our main concern for reliability is whether results are driven industry characteristics. However, we also expect that many of the finer-grained industries will behave in similar ways. We therefore create five broader industry categories – manufacturing and construction; health and education; services; agriculture; and mining, utilities, trade, and logistics. We use these broad categories to account for industry-related effects in the analyses.

Public-sector employers generally fell into the manufacturing, construction, health, education, utilities, and professional services industries. Non-profit organizations tended to be in the health and education industries. Finally, private-sector employers are generally in the manufacturing, construction, health, and professional services industries.

Table 2: Respondents by industry

Industry Category	Industry	Respondents
Manufacturing and construction	Manufacturing	29.4%
	Construction	17.7%
Health and education	Educational services	11.8%
	Health care, social assistance	11.3%
Services	Professional, scientific, technical services	7.0%
	Finance and insurance	2.8%
	Accommodation, food services	2.1%
	Central Admin. Office activity	1.7%
	Arts, entertainment, recreation	1.6%
	Information	1.0%
	Real estate, rental, leasing	0.5%
	Company/enterprise management	0.2%
Mining, utilities, logistics, and trade	Utilities	3.7%
	Transportation, warehousing	2.8%
	Retail trade	1.7%
	Waste Management	1.0%
	Wholesale trade	0.3%
	Mining	0.2%
Agriculture	Agriculture	2.8%
Other	Other	0.3%

Concerning employer demographics, we report racial information in terms of the percentage of white FTE. Likewise, for gender, we report the percentage of male FTE. As is often the case with sensitive demographic variables, these questions were left blank by a large proportion of respondents (34% and 23% respectively). Of the respondents who did provide answers to these questions, over one-third report at least 90% white workers, with 86% of companies employing mostly white workers. This is likely an

artefact of region and industry. Similarly, the fact that almost half of the companies who responded to the survey are over 80% male is likely due to the high preponderance of responses from traditionally male industries, manufacturing and construction in particular. As a result, we focus on analytical results that report how employers' training behavior and incentives vary by race and gender, not descriptive results.

## 2.1.2 Training program characteristics

We looked at four training program types:

1. Apprenticeships
2. On-the-job (OTJ) training
3. Professional development (PD)
4. Internships

Respondents chose which category their training programs fall into, so training program types are self-reported and based on respondents' definitions.

The average employer in the sample has 2.2 training programs and we designed the survey to collect data at the program level, so we reshaped the data to the program level for our main analyses. The sample includes 1,585 programs, shown by type in Table 3.

Table 3: Sample by program type

Program Type	Programs in Sample
Apprenticeship	391
OTJ Training	523
PD	363
Internship	298
<i>Other (results not reported)</i>	10
<b>Total</b>	<b>1585</b>

PD and OTJ training programs generally serve more participants when they exist (median 13 and 12 per employer, respectively), with internships and apprenticeships serving fewer (median 3 and 2, respectively). Apprenticeships are by far the longest in duration (median 24 months), compared to the other types which are all typically shorter than one year (median 9 months for OTJ training and PD, median 3 months for internships).

Private-sector employers had slightly more training programs (2.4) than public-sector (2.1) and non-profit (2.0) employers. All three sectors offer OTJ training at similar rates, while non-profits tend to offer fewer apprenticeships and more PD and internships.

Different training programs are offered to age groups at different rates. In this sample, apprenticeships are typically offered to youth (up to age 24) or young adults (25-34). OTJ training and PD are offered to all age groups. Internships tend to focus on youth.

Finally, we include a dummy variable for whether the demographics of the training program—in terms of race and gender—are like or unlike the demographics of the employer. We have information on this from 83% of programs. Of these, a majority – 62% – are demographically like the employer as a whole,

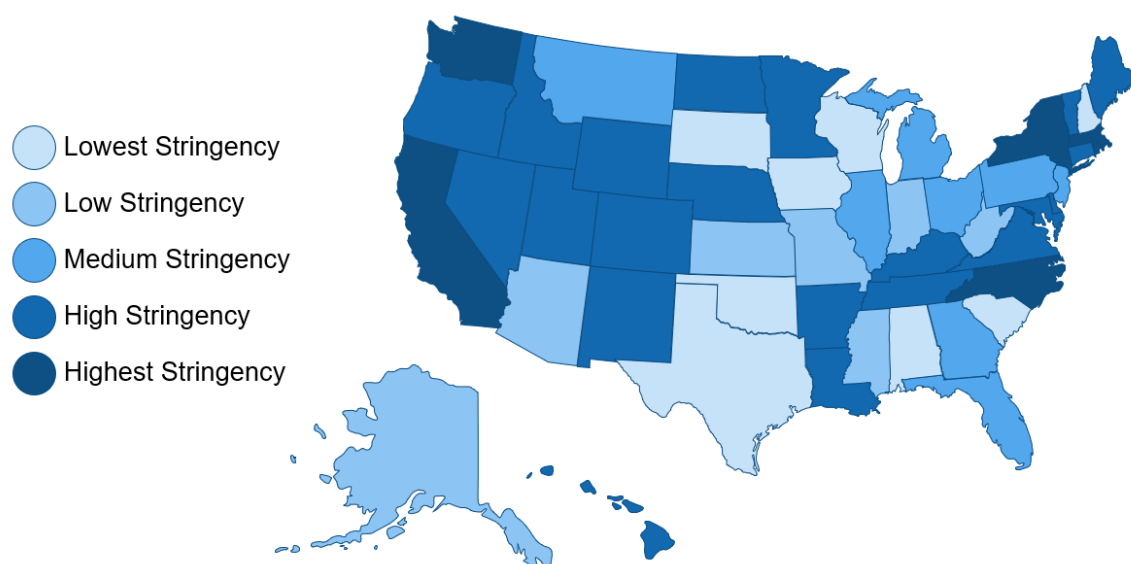
while 10% differ. In remaining cases, respondents indicated they were unsure whether the demographics of the program differed or not. Because employers in the sample are generally white and male, we can cautiously interpret different programs as being more diverse.

### 2.1.3 COVID-19 impact

We include three metrics for COVID-19's impact on employers: regulatory stringency, employers' reported impact to date, and employers' expected impact in the next year. We also examine how the pandemic has changed employers' incentives to train by looking at changes in skills supply and demand.

Oxford University's Blavatnik School of Government has been collecting and reporting data on government responses to COVID-19 throughout the pandemic, and published stringency numbers from January 2020 to April 2021<sup>11</sup>. They rank US states on the amount of time they have spent at high levels of stringency. We use this ranking to create a one-to-five-point scale from the lowest stringency to highest. Figure 1 shows stringency by state, which we include to control for required closings, stay-at-home orders, and other factors that vary by state and may disrupt employers' training or change their incentives.

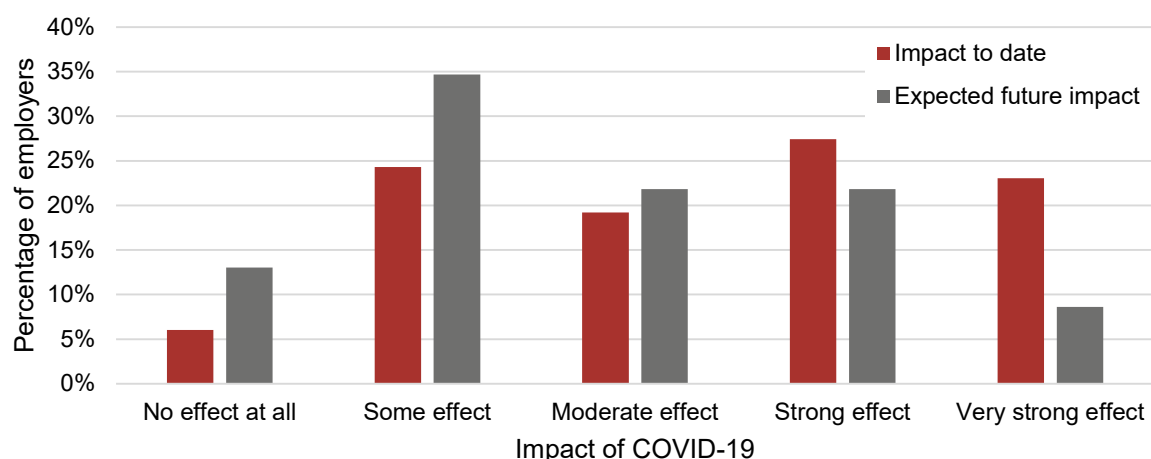
Figure 1: COVID-19 stringency by state according to Hale et al. (2021).



We also capture self-reported data on how much each employer has already been impacted by the pandemic and how much it expects to be impacted over the next year. These self-reported data are not precise in terms of actual impact, but they accurately capture how much employers feel the pandemic has affected them or will affect them. The average employer reports an impact to date of 3.4 and an expected impact of 2.8. Figure 2 shows the distribution of both impact scores.

<sup>11</sup> Hale, T., Atav, T., Hallas, L., Kira, B., Phillips, T., Petherick, A., & Pott, A. (2020). Variation in US states responses to COVID-19. Blavatnik School of Government. <https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19>

Figure 2: Distribution of self-reported COVID-19 impact on employers to date and in the next year



## 2.2 Analytical Method

We calculated two models for each research question: M1 includes the main variables only, and M2 includes those plus additional variables related to demographics and industry. We do this because some of the demographic questions were difficult to answer, so we have larger sample sizes in M1 without them. We present results for both models in all results tables, including the specific N for each model and outcome. Table 4 shows the explanatory variables and how they are defined.

Table 4: Explanatory variables

Variable	Definition*
<b>Main variables (Model 1)</b>	
Sector	3 categories: <b>public</b> , private, non-profit
Size	3 categories: <b>small</b> (1-49 FTE), medium (50-249 FTE), large (250+ FTE)
Age group	2 categories: <b>trains youth</b> , does not train youth
Program type	5 categories: apprenticeship, <b>OTJ training</b> , PD, internship, other
<b>Additional variables (added in Model 2)</b>	
Program demographics	2 categories: <b>same as employer</b> , different from employer
Employer racial diversity	Continuous: % white FTE
Employer gender diversity	Continuous: % male FTE
Industry	5 categories: <b>mining, utilities, logistics and trade</b> ; agriculture; services; health and education; manufacturing and construction
State	Account for state-level clustering of responses (only in state-nested models)
<b>Specific variables for COVID-19-related questions</b>	
COVID-19 stringency**	1-5-point scale: 1 = lowest stringency, 5 = highest stringency
COVID-19 impact to date on employer	1-5-point scale: 1 = no impact, 5 = very strong impact
Expected COVID-19 impact on employer in the next year	1-5-point scale: 1 = no impact, 5 = very strong impact
*Reference categories marked in bold	
**COVID-19 stringency from Oxford database <sup>12</sup>	

<sup>12</sup> Ibid.

We used a combination of Ordinary Least Squares (OLS) regression and state-nested random-intercept regression (hierarchical linear models) depending on whether standard errors clustered at the state level. Program value and quality outcomes are analyzed using simple OLS after testing for state-level inter-cluster correlation, and all other analyses are done with hierarchical linear models.

## 2.2.1 Non-COVID-related outcomes

For the outcomes related to reasons employers train, program value, and program quality, we calculate models without COVID-19 impact variables. Therefore, M1 is:

$$1. Y_{p,e} = \beta_0 + \beta_1 type_p + \beta_2 sector_e + \beta_3 size_e + \beta_4 youth_p + \varepsilon_{p,e} (+ \alpha_{s,p,e})$$

Where  $Y_{p,e}$  is the average value or quality determinant for program  $p$  at employer  $e$ .  $\beta_0$  is the baseline.  $Type_p$  is the program type (five categories),  $sector_e$  is the sector (three categories),  $size_e$  is firm size (three categories), and  $youth_p$  is a dummy for whether the program trains youth. Finally,  $\varepsilon_{p,e}$  is the error term for the individual programs. In circumstances where we use a state-level random-intercept model,  $\alpha_{s,p,e}$  represents the random error associated with the deviation of the state-level intercept from the over-all intercept.

M2 takes the same format and adds demographic and industry variables:

$$2. Y_{p,e} = \beta_0 + \beta_1 type_p + \beta_2 sector_e + \beta_3 size_e + \beta_4 youth_p + \beta_5 demographic_p + \beta_6 race_e + \beta_7 gender_e + \beta_8 industry_e + \varepsilon_{p,e} (+ \alpha_{s,p,e})$$

Where  $demographic_p$  is a dummy for whether the program is different to the employer in terms of race and gender characteristics,  $race_e$  is the percentage of white FTE at the employer, and  $gender_e$  is the percentage of male FTE at the employer.  $Industry_e$  is the employer's industry category.

## 2.2.2 COVID-related outcomes

To examine the effect of COVID-19 on employer-provided training in terms of disruption, trainees' skills loss, changes to training modalities, and incentives to train, we include variables related to COVID-19. Therefore, we use a version of (1) for a given program  $p$  at employer  $e$  in state  $s$  with additional variables for state-level COVID stringency ( $stringency_s$ ) and employers' reported impact of COVID-19 to date ( $ImpactToDate_e$ ) and in the next year ( $FutureImpact_e$ ). Therefore, M1 is:

$$3. Y_{p,e,s} = \beta_0 + \beta_1 type_p + \beta_2 sector_e + \beta_3 size_e + \beta_4 youth_p + \beta_5 stringency_s + \beta_6 ImpactToDate_e + \beta_7 FutureImpact_e + \varepsilon_{p,e,s} (+ \alpha_{s,p,e})$$

M2 is the same plus variables demographics and industry:

$$4. Y_{p,e} = \beta_0 + \beta_1 type_p + \beta_2 sector_e + \beta_3 size_e + \beta_4 youth_p + \beta_5 stringency_s + \beta_6 ImpactToDate_e + \beta_7 FutureImpact_e + \beta_8 demographic_p + \beta_9 race_e + \beta_{10} gender_e + \beta_{11} industry_e + \varepsilon_{p,e,s} (+ \alpha_{s,p,e})$$

## 3 Results

### 3.1 Why Employers Train

Finding skilled workers is a key issue for American employers. In this sample of employers, 80% state that a lack of qualified or skilled employees affects their growth. This sample is non-representative, but the number matches previous findings for that question<sup>13</sup>. For 31% of employers, skills mismatch affects growth significantly. 24% report moderate effects on growth, and 25% report that the lack of skilled or qualified workers affects growth a little. Only 12% report no effect at all, with the remaining 8% not answering the question.

#### 3.1.1 How employers find skills

This study focuses on training, but training is just one of many strategies employers can use to get the skilled workers they need. We asked employers what type of skills they need and how important various strategies are to them finding the workers they need. Table 5 is a simple cross-tabulation of recruiting strategies by skill type, showing how important employers consider each skill depending on the recruiting strategy they use. Thus, it shows which skills employers are looking for when they use different strategies.

Within-company hiring is the most important recruiting strategy (41% of employers rate it as “extremely” or “very” important), and 22% of companies report that hiring under-qualified people and training them is a key recruiting strategy—the same as hiring from 4-year colleges and paying relatively high wages to attract workers. All skill types are rated “extremely” or “very” important by most employers, but problem-solving skills (77%) and job-related practical skills (74%) are the most important. Soft skills (62%) and job-related knowledge (59%) are next, followed by advance conceptual skills and knowledge (53%) and advanced technical skills (52%).

The shading in the central cells of Table 5 shows which skills employers look for when they use a given recruiting strategy. Specifically, the shading is darker when the skill type is more important given that the employer reports the strategy is “very important” or “extremely important.” The numbers also reflect this, showing the mode of skill importance (on a 1-5-point scale) given high strategy importance. In most recruiting strategies, employers follow the pattern of finding all skills important with an emphasis on job-related practical skills and soft skills—this includes employers who train their own skilled workers. Job-related knowledge and advanced conceptual knowledge are more important among employers who hire from 4-year colleges and universities, while employers who hire from within the company are most focused on job-related knowledge and advanced technical skills.

Even using various strategies to find and attract skilled workers, employers generally are not able to hire workers whose skills match their needs precisely. Overall, employers report that new hires’ skills at least meet their requirements in only 57% of cases on average. This rate is the highest for problem-solving skills (62%) and soft skills (60%), slightly lower for job-related knowledge and skills (59% and 58%, respectively), and lowest for advanced technical skills and advanced conceptual skills or knowledge

<sup>13</sup> Renold, U., Bolli, T., Caves, K., & Buergi, J. (2017). Training for growth: Skills shortage and companies’ willingness to train in Colorado. An application of the KOF Willingness to Train Survey (No. 94). KOF Studies. <https://www.research-collection.ethz.ch/handle/20.500.11850/164859>

(both 52%). When the employers in this sample hire a new worker, it takes a median of 16 weeks and an average of 24 weeks for that worker to reach full productivity, with the mode response at 52 weeks. Although half of new hires are up to speed within four months, many companies report spending a year or more investing in not-fully-productive new hires.

Table 5: Skill type importance by strategies for finding skilled workers

Recruiting strategy	Skill type						Strategy is "very" or "extremely" important
	Job-related knowledge	Job-related practical skills	Problem-solving skills	Advanced technical skills	Advanced conceptual knowledge/skills	Soft skills	
Hiring from 2-year community/technical colleges	4	5	5	3	4	5	27%
Hiring from 4-year colleges/universities	5	5	5	4	5	5	22%
Hiring from secondary/high school	4	5	5	4	3	5	29%
Hiring from other companies	4	5	4	4	4	5	24%
Hiring from within the company	5	5	4	5	4	5	41%
Hiring under-qualified people and training them	4	5	4	4	3	5	22%
Screening potential new hires through short-term positions	5	5	5	4	3	5	17%
Paying above-market wages to attract new hires	4	5	5	4	4	5	22%
Skill is "very" or "extremely" important	59%	74%	77%	52%	53%	62%	

*Note: Importance of recruiting strategies and skills are on a 1-5-point scale where 1= "not important at all," 2= "slightly important," 3= "moderately important," 4="very important," and 5="extremely important." The colored cells show the mode skill importance (columns) when the recruiting strategy (rows) is "very" or "extremely" important. Cells are colored according to skill importance, with darker blue representing more importance.*

### 3.1.2 Reasons to train

Employers can use training as a strategy to get the skills they need, to improve the skill level of new hires, and for other reasons. We asked employers about nine potential reasons for training:

1. To retain our employees
2. To replace retiring skilled workers
3. To save on recruitment costs
4. To screen new hires (a "try before you buy" approach)
5. To help us shift from degree-based hiring to skills-based hiring
6. To build a diverse workforce
7. To help us hire/retain local talent
8. Because it's the best way to get workers with the right skills
9. Because school/college/university graduates do not meet our needs

For each of these, we examine which training programs companies use to meet the goal and how employer and training program characteristics play into that relationship. Table 6 and Table 7 show results for reasons to train and training approaches.

Standard errors showed some evidence of clustering at the state level, so we use state-nested models in this analysis. Recall that all the regressions in this report assign a reference category for each of the categorical or dummy variables, and the constant is based on these reference categories. Differences across other categories are with respect to this baseline value. The reference training program type is

OTJ training, so the tables show how different the other program types are. The reference sector is the public sector. The reference employer size is small (fewer than 50 FTE). The reference program does not train youth.

Because M2 includes more variables than M1, there are always fewer observations in M2. We show both models because M1 has greater coverage and a larger sample size while M2 has more relevant variables. The reference industry is mining, utilities, trade, and logistics. The variables related to employer race and gender demographics are continuous variables, and the results show how dependent variables change as the employer is 10% more white or 10% more male.

The most important reason to train in the baseline specification is what we would expect based on training as a skills-acquisition strategy: it is the best way to get the right skills. Employee retention and hiring/retaining local talent are also highly important. Building a diverse workforce, replacing retiring skilled workers, and graduates not meeting skills needs are all moderately important. The least important reasons that employers offer training at baseline are shifting towards skills-based hiring, screening new hires, and—least important—saving on recruitment costs.

Training type, employer characteristics, and demographics play into why employers train. We would expect that employers would use different training program modalities to meet different goals. However, we find limited difference across training program types. Employers who offer apprenticeships do not have significantly different reasons for that choice than the baseline of OTJ training. PD is also offered for the same reasons as the baseline, with the exception that employers offering PD are more interested in saving on recruitment costs. They seem to be interested in employee retention, but the effect disappears in M2. Employers who offer internships are significantly less interested in employee retention. Internship employers seem to value getting the right skills, but the effect disappears in M2. Unlike our expectations, employers do not consistently differentiate among the function of various training types.

Training programs that include youth are driven by different motivations than those not training youth. Youth-inclusive programs are driven more by hiring and retaining local talent and retaining employees. There are effects in M1 where youth-inclusive programs are more driven by building a diverse workforce, saving on recruitment costs, and screening new hires, but those disappear in M2. Interestingly, employers who train youth do not seem to be motivated by a desire to shift from degree-based to skills-based hiring or by getting the right skills, which is somewhat surprising.

Employer characteristics affect reasons for training. Non-profit employers are much less interested in shifting from degree-based to skills-based hiring (more than 0.6 points lower). They seem less interested in getting the right skills, training because graduates do not meet their needs, employee retention, and replacing retirees, but these effects all disappear in M2. Compared to the baseline public-sector employers, private-sector employers value hiring and retaining local talent, training because graduates do not meet their needs, employee retention, getting the right skills, and saving on recruitment costs more. They seem to be less interested in building a diverse workforce and more interested in replacing retirees and screening new hires, but those effects disappear in M2.

Medium- and large-sized employers are more interested than their small counterparts in employee retention and replacing skilled workers, and less interested in using training to screen potential new hires. They are less motivated to train because graduates do not meet their needs. Large employers are less interested than small or medium employers in shifting to skills-based hiring. Large employers are more motivated by building a diverse workforce, although medium-sized employers are also more interested



in this once additional variables are added in M2. Finally, medium-sized employers are more interested in local talent (large employers also in M2), less motivated to train because it is the best way to get skilled workers, and (M2 only) more interested in saving on recruitment costs.

When we add additional variables in M2, the sign of coefficients is stable though we see some movement in the effects sizes themselves. There are significant differences by industry. Employers in agriculture generally value all reasons to train less than the baseline (mining, utilities, trade, and logistics) but the only significant differences are shifting to skills-based hiring (-1.4 points, a very large effect), building a diverse workforce (-1.1 points), hiring/retaining local talent (-0.9 points), and getting the right skills (-0.6 points). All of these effects sizes are very large. The services industry is less motivated to train to shift from degree-based to skills-based hiring, to replace retiring skilled workers, or because it is the best way to get skilled workers, but more motivated to train as a method of screening new hires. In the health and education industries, skills-based hiring, local talent, getting the right skills, replacing retirees, and saving recruitment costs are all less important than the baseline. Finally, the manufacturing and construction industry is less motivated by skills-based hiring and local talent.

We would expect to see that employers who train to build a diverse workforce would have training programs that differ from the employer demographically. To a lesser extent, we may also see this in companies that train to shift towards skills-based hiring instead of degree-based hiring. We do indeed see this pattern: employers with training programs that are demographically different from the organization as a whole value building a diverse workforce and shifting to skills-based hiring more than their counterparts with training programs that match the organization demographically. Employers with demographically different training programs also place more value on screening new hires and training because graduates do not meet their needs.

As employers are more white, they value skills-based hiring and a diverse workforce less. They are also less likely to state that they train because graduates do not meet their skills needs. As they are more male, employers value skills-based hiring more but getting the right skills and saving on recruitment costs less.

Table 6: Reasons to train (part 1)

	<i>Dependent variable:</i>							
	Employee retention		Replace retiring skilled workers		Save on recruitment costs		Screen new hires	
	(1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	3.853*** (0.088)	3.711*** (0.231)	3.078*** (0.149)	3.436*** (0.292)	2.538*** (0.149)	2.991*** (0.336)	2.584*** (0.140)	2.430*** (0.301)
Apprenticeship	0.017 (0.068)	0.006 (0.080)	0.136 (0.093)	0.113 (0.107)	-0.012 (0.101)	-0.016 (0.121)	0.021 (0.091)	-0.045 (0.112)
Professional development	0.127* (0.071)	0.119 (0.086)	0.022 (0.097)	0.096 (0.114)	0.215** (0.105)	0.288** (0.130)	-0.077 (0.095)	-0.098 (0.120)
Internship	-0.216*** (0.076)	-0.180** (0.091)	0.015 (0.104)	0.088 (0.120)	0.055 (0.112)	0.144 (0.137)	0.120 (0.101)	0.133 (0.126)
Nonprofit sector	-0.222** (0.087)	0.140 (0.112)	-0.373*** (0.119)	-0.007 (0.147)	0.033 (0.130)	0.322* (0.167)	-0.158 (0.117)	0.113 (0.154)
Private sector	0.133** (0.062)	0.142* (0.080)	0.227*** (0.084)	0.022 (0.105)	0.335*** (0.092)	0.238** (0.120)	0.192** (0.083)	0.135 (0.110)
Medium size	0.227*** (0.063)	0.367*** (0.072)	0.563*** (0.085)	0.492*** (0.096)	0.083 (0.093)	0.219** (0.109)	-0.385*** (0.084)	-0.408*** (0.101)
Large size	0.235*** (0.065)	0.182** (0.086)	0.653*** (0.091)	0.535*** (0.113)	0.152 (0.098)	-0.097 (0.128)	-0.503*** (0.088)	-0.794*** (0.117)
Trains youth	0.175*** (0.058)	0.187*** (0.069)	-0.024 (0.080)	-0.065 (0.092)	0.204** (0.087)	0.023 (0.105)	0.166** (0.078)	0.146 (0.097)
Agriculture		-0.190 (0.219)		-0.222 (0.291)		-0.284 (0.332)		-0.429 (0.300)
Services		0.189 (0.134)		-0.492*** (0.178)		0.003 (0.202)		0.363* (0.186)
Health and education		-0.103 (0.146)		-0.776*** (0.193)		-0.549** (0.219)		0.034 (0.203)
Manufacturing and construction		-0.006 (0.118)		0.135 (0.156)		-0.029 (0.177)		0.210 (0.164)
Program demographic		0.179* (0.106)		0.031 (0.142)		0.163 (0.160)		0.405*** (0.148)
Employer white		-0.023 (0.015)		-0.012 (0.019)		0.028 (0.022)		-0.031 (0.020)
Employer male		0.022 (0.016)		0.029 (0.022)		-0.065*** (0.025)		0.037 (0.023)
Observations	1,484	982	1,476	980	1,471	979	1,473	984
Log Likelihood	-2,091.239	-1,361.894	-2,531.270	-1,630.265	-2,640.422	-1,750.275	-2,491.575	-1,683.365
Akaike Inf. Crit.	4,206.478	2,763.788	5,086.539	3,300.530	5,304.844	3,540.550	5,007.149	3,406.730
Bayesian Inf. Crit.	4,270.108	2,861.580	5,150.104	3,398.281	5,368.368	3,638.281	5,070.690	3,504.563

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Note:

Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

Table 7: Reasons to train (part 2)

	<i>Dependent variable:</i>									
	Shift from degree- to skills-based hiring		Build a diverse workforce		Hire/retain local talent		Best way to get right skills		Graduates don't meet needs	
	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	2.750*** (0.167)	3.763*** (0.333)	3.281*** (0.149)	3.989*** (0.301)	3.813*** (0.105)	4.278*** (0.222)	3.997*** (0.114)	4.434*** (0.246)	2.993*** (0.176)	3.579*** (0.330)
Apprenticeship	0.112 (0.093)	0.083 (0.109)	0.085 (0.089)	0.074 (0.104)	0.030 (0.067)	-0.003 (0.079)	0.018 (0.073)	-0.009 (0.086)	0.094 (0.093)	-0.025 (0.109)
Professional development	-0.042 (0.097)	-0.068 (0.117)	0.107 (0.093)	0.149 (0.112)	0.039 (0.070)	0.048 (0.085)	-0.072 (0.076)	-0.057 (0.093)	-0.033 (0.097)	-0.052 (0.117)
Internship	-0.013 (0.103)	-0.034 (0.123)	-0.065 (0.099)	-0.103 (0.118)	-0.070 (0.074)	-0.003 (0.089)	-0.145* (0.081)	-0.087 (0.098)	0.005 (0.103)	0.040 (0.123)
Nonprofit sector	-0.632*** (0.120)	-0.648*** (0.153)	0.005 (0.115)	0.158 (0.146)	-0.070 (0.086)	0.046 (0.110)	-0.201** (0.094)	0.060 (0.120)	-0.553*** (0.121)	-0.100 (0.153)
Private sector	-0.078 (0.085)	-0.150 (0.109)	-0.211*** (0.081)	-0.067 (0.104)	0.261*** (0.061)	0.322*** (0.079)	0.177*** (0.066)	0.260*** (0.086)	0.271*** (0.085)	0.246** (0.109)
Medium size	-0.071 (0.085)	-0.025 (0.099)	0.090 (0.082)	0.163* (0.095)	0.123** (0.062)	0.216*** (0.072)	-0.153** (0.067)	-0.209*** (0.078)	-0.279*** (0.086)	-0.291*** (0.099)
Large size	-0.201** (0.091)	-0.586*** (0.117)	0.346*** (0.087)	0.195* (0.111)	0.144** (0.065)	0.042 (0.084)	0.043 (0.071)	-0.027 (0.092)	-0.441*** (0.091)	-0.750*** (0.117)
Trains youth	-0.064 (0.080)	-0.140 (0.095)	0.193** (0.076)	0.127 (0.091)	0.160*** (0.058)	0.135** (0.069)	-0.0004 (0.063)	-0.026 (0.075)	-0.042 (0.080)	-0.082 (0.095)
Agriculture		-1.418*** (0.306)		-1.132*** (0.290)		-0.889*** (0.215)		-0.634*** (0.236)		-0.166 (0.306)
Services		-0.347* (0.183)		0.116 (0.175)		-0.201 (0.133)		-0.504*** (0.145)		-0.272 (0.183)
Health and education		-0.495** (0.199)		-0.246 (0.190)		-0.314** (0.144)		-0.584*** (0.158)		-0.733*** (0.199)
Manufacturing and construction		-0.335** (0.160)		-0.219 (0.154)		-0.258** (0.117)		-0.134 (0.127)		0.150 (0.161)
Program demographic		0.370** (0.146)		0.410*** (0.139)		0.120 (0.106)		0.157 (0.116)		0.272* (0.146)
Employer white		-0.089*** (0.020)		-0.074*** (0.019)		-0.022 (0.014)		0.005 (0.016)		-0.065*** (0.020)
Employer male		0.039* (0.022)		0.005 (0.022)		-0.002 (0.016)		-0.032* (0.018)		-0.0003 (0.022)
Observations	1,473	980	1,479	982	1,476	984	1,478	982	1,464	981
Log Likelihood	-2,526.728	-1,658.881	-2,472.331	-1,618.810	-2,049.182	-1,353.947	-2,180.614	-1,436.890	-2,512.711	-1,661.718
Akaike Inf. Crit.	5,077.455	3,357.761	4,968.662	3,277.619	4,122.364	2,747.894	4,385.228	2,913.781	5,049.421	3,363.435
Bayesian Inf. Crit.	5,140.996	3,455.512	5,032.252	3,375.411	4,185.929	2,845.726	4,448.809	3,011.572	5,112.888	3,461.206

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Note:

Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

## 3.2 Training Program Value and Quality

A training program has value for participants when they earn something through their participation in the program. We measured six types of value:

1. Registration (for apprenticeship only)
2. Company-specific credentials
3. External credentials
4. Occupational licenses
5. Postsecondary credit
6. Other credit

Additionally, we include five program quality measures:

1. Wages
2. Degrees (only for credit-bearing programs)
3. Trainers
4. Curricula
5. Quality control

For each of these, we assessed which program types, sectors, employer sizes, and age groups most commonly offer high-value or high-quality programs. We also included industry, program demographics, and employer racial and gender demographics in the second model specification. Standard errors did not cluster at the state level, so we used simple OLS regressions. Table 9 and Table 10 show the results for each value or quality metric and model specification.

### 3.2.1 Apprenticeship registration

Apprenticeship programs have a unique form of value: registration through the United States Department of Labor. For apprenticeship programs specifically, we asked employers if their program leads to a nationally-recognized credential from the U.S. Department of Labor. Table 8 shows the results for apprenticeship registration.

In the baseline specification, just over half of programs categorized by employers as apprenticeships are registered. More are registered in medium-sized and large employers. Program age group and demographics are irrelevant, as are employer demographics. However, employers in the services industries are so much less likely to register their apprenticeship programs that it completely negates the baseline level—these programs are almost never registered.

Table 8: Apprenticeship registration

	<i>Dependent variable:</i>	
	Apprenticeship registration	
	(M1)	(M2)
Constant	0.576*** (0.076)	0.524*** (0.192)
Nonprofit sector	0.030 (0.103)	0.085 (0.116)
Private sector	0.017 (0.061)	−0.017 (0.075)
Medium size	0.117* (0.064)	0.163** (0.073)
Large size	0.177*** (0.067)	0.203** (0.088)
Trains youth	−0.025 (0.062)	−0.003 (0.070)
Agriculture		−0.244 (0.181)
Services		−0.522*** (0.130)
Health and education		−0.180 (0.148)
Manufacturing and construction		−0.047 (0.105)
Program demographic		0.094 (0.087)
Employer white		0.003 (0.013)
Employer male		0.017 (0.017)
Observations	325	222
R <sup>2</sup>	0.025	0.174
Adjusted R <sup>2</sup>	0.010	0.123
Residual Std. Error	0.477 (df = 319)	0.445 (df = 208)
F Statistic	1.663 (df = 5; 319)	3.377*** (df = 13; 208)
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01
<i>Note:</i>		Reference categories are as follows: public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

### 3.2.2 Program value

As a high-level overview of program value in Table 9, we find that company-specific credentials and external credentials are common in the baseline specification, while occupational licenses and other credit are moderately common and postsecondary credit is least common. However, there are significant deviations from that baseline when we look at different program types, firm characteristics, and additional variables.

Program value varies significantly by training program type: OTJ training, which is the baseline program type, offers all forms of value except company-specific credentials less often than apprenticeship and PD. The differences can be stark—for example, apprenticeships are offer postsecondary credit more

than 25% more often than OTJ training does. Only internships offer less value than OTJ training, granting fewer company-specific credentials, external credentials, and occupational. However, internships offer more postsecondary and other credit. Programs that train youth offer fewer external credentials and occupational licenses.

Employer characteristics also affect training program value. Larger companies offer more value in their training programs. Medium and large employers offer more company-specific credentials and postsecondary credit than small employers do. Large employers and potentially medium employers (only in M2) offer more external credentials. Medium employers and potentially large employers (only in M2) offer more occupational licenses. Large employers may offer more other credit (only in M2) than small employers do.

The effect of employers' sector is less systematic. Non-profit employers appear to offer fewer company-specific credentials and occupational licenses than the public sector, but the effect disappears when we add controls and seems to be more related to industry than sector. Non-profit employers clearly offer more postsecondary credit than the public sector does. Private-sector employers offer fewer company-specific credentials than the public sector. The private sector appears to offer fewer occupational licenses, but again this effect is more related to industry than sector.

M2 adds industry and demographic variables. Coefficients for all variables are generally stable after the additional variables in M2. The demographic variables generally insignificant except for external credentials, which are more common when the training program is different from the employer's overall racial and/or gender composition and more common when the employer is more male.

Industry has a significant impact on program value. The agriculture industry grants company-specific credentials, external credentials, and occupational licenses less often than the baseline (mining, utilities, trade, and logistics). The services industry offers less of every program value metric except occupational licenses, all between 15-20% lower than the baseline level. Employers in the health and education industry offer fewer company-specific credentials in their training programs. The manufacturing and construction industry offers external credentials less often than the baseline, but otherwise it is not significantly different.

### 3.2.3 Program quality

For program quality in Table 10, the baseline specification typically has wages, offers degrees in credit-bearing programs, has trainers, and has a curriculum. Quality control is less common. In this model, the outcome "degrees" applies only to programs that offer some kind of credit.

Training program type is again a significant factor. Compared to the baseline of OTJ training, all program types are generally similar in terms of whether they offer wages. However, apprenticeships offer more degrees, trainers, curricula, and quality control. The differences in effects size can be large—apprenticeships offer quality control nearly 50% more than OTJ training does. PD programs are less likely to have trainers but more likely to have curricula and quality control. Internships are similar to OTJ training but have curricula and quality control more often. Overall, apprenticeships and then PD are the most robust in terms of program quality, with OTJ training and internships further behind. Programs that train youth are not significantly different from non-youth programs except for having less quality control.

Employer factors affect a few quality outcomes, although sector does not drive training quality. Non-profit employers are approximately 30% less likely than the public sector to have credit-bearing programs that lead to degrees. They are slightly less likely to pay wages, but that effect disappears with controls. They do not initially appear to be different regarding quality control, but with controls added, non-profit employers are more likely than the public sector to have quality control. The private sector is like the public sector for trainers until controls are added, then it offers them slightly less often. The private sector appears more likely to pay wages without controls, but that effect disappears completely with controls in M2.

Large and medium-sized employers can generally offer higher program quality. Both pay wages and offer curricula more often than small employers. Large and medium employers' credit-bearing training programs lead to degrees more often than small employers', but the effect disappears with controls in M2. The presence of trainers and quality control does not appear to vary by firm size.

Coefficients are generally stable when we add the additional variables for industry and demographics, but the additional variables are occasionally significant. Employers that are more white pay their trainees more often, and those that are more male have quality control more often. When the program's race and gender composition is different from the employer, it has a curriculum less often. The availability of trainers, curricula, and quality control do not vary by industry. The services and health/education industries pay wages during training less often than the baseline (mining, utilities, trade, and logistics). The service industry's training programs with credit lead to degrees less often.

Table 9: Training program value

	<i>Dependent variable:</i>									
	Company-specific credential		External credential		Occupational license		Post-secondary credential		Other credential	
	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	0.680*** (0.039)	0.737*** (0.104)	0.619*** (0.040)	0.552*** (0.106)	0.518*** (0.040)	0.301*** (0.108)	0.242*** (0.041)	0.133 (0.106)	0.439*** (0.042)	0.496*** (0.112)
Apprenticeship	-0.007 (0.035)	-0.013 (0.042)	0.144*** (0.034)	0.132*** (0.042)	0.094*** (0.036)	0.112*** (0.042)	0.271*** (0.035)	0.256*** (0.042)	0.192*** (0.037)	0.188*** (0.044)
Professional development	0.039 (0.035)	0.038 (0.044)	0.120*** (0.036)	0.110** (0.045)	0.132*** (0.037)	0.103** (0.046)	0.172*** (0.036)	0.189*** (0.045)	0.163*** (0.038)	0.144*** (0.047)
Internship	-0.247*** (0.038)	-0.217*** (0.047)	-0.136*** (0.038)	-0.135*** (0.047)	-0.147*** (0.039)	-0.126*** (0.048)	0.281*** (0.038)	0.290*** (0.046)	0.099** (0.039)	0.103** (0.048)
Nonprofit sector	-0.207*** (0.043)	-0.076 (0.055)	0.010 (0.043)	0.073 (0.055)	-0.076* (0.044)	-0.019 (0.056)	0.093** (0.043)	0.184*** (0.055)	0.056 (0.045)	0.086 (0.058)
Private sector	-0.086*** (0.030)	-0.081** (0.040)	-0.041 (0.031)	0.012 (0.041)	-0.081*** (0.032)	0.022 (0.042)	-0.036 (0.031)	0.028 (0.041)	-0.022 (0.032)	0.066 (0.043)
Medium size	0.065** (0.031)	0.120*** (0.037)	0.034 (0.031)	0.093** (0.037)	0.066** (0.032)	0.094** (0.038)	0.066** (0.032)	0.105*** (0.037)	0.046 (0.033)	0.063 (0.039)
Large size	0.074** (0.032)	0.136*** (0.043)	0.075** (0.032)	0.128*** (0.043)	0.051 (0.033)	0.103** (0.044)	0.167*** (0.032)	0.257*** (0.043)	0.020 (0.033)	0.117** (0.045)
Trains youth	-0.013 (0.029)	-0.035 (0.036)	-0.076*** (0.029)	-0.082** (0.036)	-0.104*** (0.030)	-0.184*** (0.036)	-0.029 (0.030)	-0.038 (0.036)	-0.002 (0.031)	-0.032 (0.038)
Agriculture		-0.240** (0.108)		-0.278*** (0.107)		-0.289*** (0.109)		-0.035 (0.107)		-0.168 (0.112)
Services		-0.184*** (0.068)		-0.150** (0.068)		-0.036 (0.071)		-0.169** (0.070)		-0.167** (0.073)
Health and education		-0.223*** (0.074)		-0.036 (0.074)		0.106 (0.076)		0.023 (0.075)		-0.038 (0.078)
Manufacturing and construction		-0.088 (0.062)		-0.117* (0.061)		-0.009 (0.064)		0.013 (0.063)		-0.068 (0.066)
Program demographic		-0.053 (0.055)		0.094* (0.055)		0.043 (0.056)		0.057 (0.055)		0.062 (0.057)
Employer white		0.002 (0.006)		-0.00004 (0.006)		0.009 (0.007)		0.006 (0.006)		0.001 (0.007)
Employer male		0.001 (0.008)		0.014* (0.008)		0.013 (0.009)		-0.001 (0.008)		-0.010 (0.009)
Observations	1,395	927	1,370	908	1,339	888	1,331	881	1,333	883
R <sup>2</sup>	0.064	0.087	0.060	0.090	0.067	0.113	0.091	0.141	0.032	0.060
Adjusted R <sup>2</sup>	0.058	0.070	0.054	0.073	0.061	0.096	0.084	0.124	0.025	0.042
Residual Std. Error	0.477 (df = 1385)	0.474 (df = 909)	0.474 (df = 1360)	0.468 (df = 890)	0.482 (df = 1329)	0.473 (df = 870)	0.474 (df = 1321)	0.464 (df = 863)	0.491 (df = 1323)	0.485 (df = 865)
F Statistic	10.481*** (df = 9; 1385)	5.096*** (df = 17; 909)	9.669*** (df = 9; 1360)	5.173*** (df = 17; 890)	10.688*** (df = 9; 1329)	6.520*** (df = 17; 870)	14.633*** (df = 9; 1321)	8.307*** (df = 17; 863)	4.813*** (df = 9; 1323)	3.276*** (df = 17; 865)

Note:

Reference categories are as follows: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01



Table 10: Training program quality

	<i>Dependent variable:</i>									
	Wages		Degree		Trainers		Curricula		Quality control	
	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	0.911*** (0.018)	0.869*** (0.046)	0.584*** (0.061)	0.705*** (0.163)	0.907*** (0.025)	1.016*** (0.058)	0.849*** (0.024)	0.866*** (0.063)	0.358*** (0.037)	0.269*** (0.099)
Apprenticeship	0.019 (0.015)	-0.0001 (0.018)	0.194*** (0.053)	0.207*** (0.067)	0.070*** (0.021)	0.066*** (0.023)	0.108*** (0.021)	0.113*** (0.025)	0.476*** (0.032)	0.462*** (0.039)
Professional development	-0.027* (0.016)	-0.017 (0.020)	0.087 (0.056)	0.084 (0.070)	-0.146*** (0.022)	-0.126*** (0.025)	0.080*** (0.022)	0.073*** (0.027)	0.205*** (0.034)	0.178*** (0.042)
Internship	-0.028* (0.017)	-0.018 (0.021)	0.049 (0.056)	0.062 (0.071)	0.021 (0.024)	0.019 (0.026)	-0.061** (0.024)	-0.072** (0.028)	0.150*** (0.036)	0.148*** (0.044)
Nonprofit sector	-0.037* (0.019)	0.020 (0.025)	-0.282*** (0.057)	-0.326*** (0.075)	0.009 (0.027)	-0.032 (0.031)	0.003 (0.027)	0.007 (0.033)	0.048 (0.041)	0.133** (0.052)
Private sector	0.030** (0.014)	-0.003 (0.018)	-0.035 (0.045)	-0.044 (0.066)	-0.025 (0.019)	-0.047** (0.022)	-0.010 (0.019)	-0.029 (0.024)	-0.036 (0.029)	-0.025 (0.038)
Medium size	0.037*** (0.014)	0.041** (0.017)	0.088* (0.047)	0.051 (0.058)	0.011 (0.020)	0.014 (0.021)	0.054*** (0.020)	0.063*** (0.022)	0.010 (0.030)	0.037 (0.036)
Large size	0.039*** (0.014)	0.058*** (0.019)	0.099** (0.044)	0.096 (0.061)	0.009 (0.020)	0.035 (0.023)	0.049** (0.020)	0.052** (0.025)	-0.016 (0.030)	-0.007 (0.040)
Trains youth	0.016 (0.013)	0.010 (0.016)	0.047 (0.044)	0.053 (0.055)	0.003 (0.018)	-0.003 (0.020)	-0.027 (0.018)	-0.036* (0.021)	-0.074*** (0.027)	-0.087*** (0.034)
Agriculture		-0.009 (0.049)		-0.073 (0.170)		-0.085 (0.061)		-0.086 (0.066)		-0.004 (0.104)
Services		-0.068** (0.030)		-0.211* (0.113)		-0.008 (0.038)		0.062 (0.041)		-0.089 (0.064)
Health and education		-0.110*** (0.033)		-0.019 (0.110)		0.003 (0.041)		0.064 (0.045)		0.084 (0.071)
Manufacturing and construction		-0.015 (0.027)		0.016 (0.097)		-0.026 (0.034)		0.036 (0.036)		0.027 (0.058)
Program demographic		-0.011 (0.024)		-0.018 (0.075)		-0.013 (0.030)		-0.084** (0.033)		0.028 (0.052)
Employer white		0.009*** (0.003)		-0.009 (0.010)		-0.005 (0.004)		-0.001 (0.004)		-0.009 (0.006)
Employer male		0.005 (0.004)		-0.007 (0.013)		-0.001 (0.005)		-0.0003 (0.005)		0.018** (0.008)
Observations	1,480	986	571	375	1,472	985	1,483	987	1,478	976
R <sup>2</sup>	0.031	0.099	0.095	0.136	0.066	0.076	0.050	0.082	0.137	0.169
Adjusted R <sup>2</sup>	0.025	0.083	0.080	0.097	0.060	0.060	0.044	0.066	0.131	0.154
Residual Std. Error	0.221 (df = 1470)	0.216 (df = 968)	0.444 (df = 561)	0.448 (df = 358)	0.308 (df = 1462)	0.271 (df = 967)	0.308 (df = 1473)	0.293 (df = 969)	0.466 (df = 1468)	0.460 (df = 958)
F Statistic	5.258*** (df = 9; 1470)	6.226*** (df = 17; 968)	6.526*** (df = 9; 561)	3.522*** (df = 16; 358)	11.392*** (df = 9; 1462)	4.697*** (df = 17; 967)	8.587*** (df = 9; 1473)	5.102*** (df = 17; 969)	25.816*** (df = 9; 1468)	11.443*** (df = 17; 958)

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Note: Reference categories are as follows: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

### 3.3 COVID-19 Training Disruption

The COVID-19 pandemic disrupted training, and the major labor market disruptions may have changed employers' incentives related to training. We investigated two outcomes for existing training programs:

1. Program disruption
2. Loss of practical skills for trainees

For program disruption, we include pausing or canceling an ongoing cohort, as well as canceling upcoming cohorts. We measured the effect on trainees' practical skills on a five-point scale as assessed by employers, where one is no skills are lost and five is complete. We add a COVID-19 stringency scale and employers' reported impact of the pandemic to date and expected impact over the next year to the variables in M1 and M2. Table 11 shows results for disruption of training programs and impact on trainees' skill development.

The constant for training disruption is significant in M1 but not in M2. With the full set of variables, we do not find a significant disruption to training caused by the COVID-19 pandemic in the baseline model. However, some characteristics of the training program, employer, and level of COVID impact do drive significant disruption effects. Internships are significantly more disrupted in both models, with roughly twice as much disruption as the baseline in M2. Training at large employers was disrupted more. Programs that are different demographically to their host employers were disrupted more. Youth-inclusive programs are not different from the baseline. Private-sector employers are less disrupted. All industries are generally equivalent except for health and education, where training was disrupted less by the pandemic. Finally, although the impact of COVID-19 to date and the stringency of regulations are insignificant, the expected future impact of the pandemic over the next year increases program disruption.

The story is generally similar for the effects of the COVID-19 pandemic on trainees' skill development, although the constant is significant so we do find an effect on skills regardless of the null effect for program disruption in general. Participants in PD programs and internships lost more skills development than the baseline. The non-profit sector is unclear, but trainees in the private sector had their skills development less affected. Firm size does not affect skills loss, nor does program age group. Trainees in the agriculture industry lost less skill development, but those in the services industry lost more. This time, greater impact of COVID-19, greater expected impact, and greater regulatory stringency are all associated with greater skills development losses for trainees.

It is somewhat surprising that the impact to date of the COVID-19 pandemic on employers and the regulatory stringency related to the pandemic are not consistently related to training disruption, and that their effects are not larger for both outcomes. Suspecting non-linear effects within the five levels of each scale, we decomposed those into categorical variables and re-ran the same analysis. Table 14 in the appendix shows the full results of that regression, and Figure 3 shows the results graphically.

Table 11: COVID-19 training disruption and impact on practical skills development

	<i>Dependent variable:</i>			
	Disruption to training		Effects on practical training	
	(M1)	(M2)	(M1)	(M2)
Constant	0.227** (0.090)	0.157 (0.143)	1.118*** (0.215)	0.873** (0.380)
Apprenticeship	0.072* (0.040)	0.041 (0.048)	0.069 (0.097)	0.102 (0.114)
Professional development	0.075* (0.042)	0.080 (0.052)	0.287*** (0.103)	0.320*** (0.124)
Internship	0.155*** (0.044)	0.151*** (0.054)	0.510*** (0.109)	0.389*** (0.130)
Nonprofit sector	-0.018 (0.053)	-0.053 (0.068)	0.271** (0.130)	-0.013 (0.169)
Private sector	-0.075** (0.036)	-0.142*** (0.048)	-0.187** (0.088)	-0.216* (0.115)
Medium size	-0.005 (0.037)	-0.014 (0.044)	-0.089 (0.092)	-0.093 (0.107)
Large size	-0.019 (0.040)	0.095* (0.051)	-0.012 (0.096)	0.196 (0.123)
Trains youth	-0.040 (0.035)	-0.021 (0.042)	0.034 (0.086)	0.083 (0.101)
Agriculture		0.020 (0.135)		-0.645** (0.326)
Services		-0.116 (0.077)		0.411** (0.188)
Health and education		-0.169* (0.092)		0.287 (0.221)
Manufacturing and construction		0.028 (0.068)		-0.002 (0.163)
Program demographic		0.115* (0.067)		0.263 (0.162)
Employer white		0.006 (0.008)		0.026 (0.020)
Employer male		-0.008 (0.010)		0.003 (0.024)
Impact of COVID-19	0.018 (0.019)	0.034 (0.023)	0.228*** (0.045)	0.156*** (0.056)
Expected future impact of COVID-19	0.058*** (0.020)	0.061** (0.025)	0.080 (0.049)	0.141** (0.061)
COVID stringency index	-0.007 (0.020)	0.013 (0.018)	0.168*** (0.048)	0.165*** (0.063)
Observations	1,015	685	987	671
Log Likelihood	-713.394	-492.398	-1,550.403	-1,042.914
Akaike Inf. Crit.	1,456.788	1,030.796	3,130.805	2,131.828
Bayesian Inf. Crit.	1,530.628	1,134.973	3,204.225	2,235.530

Note:

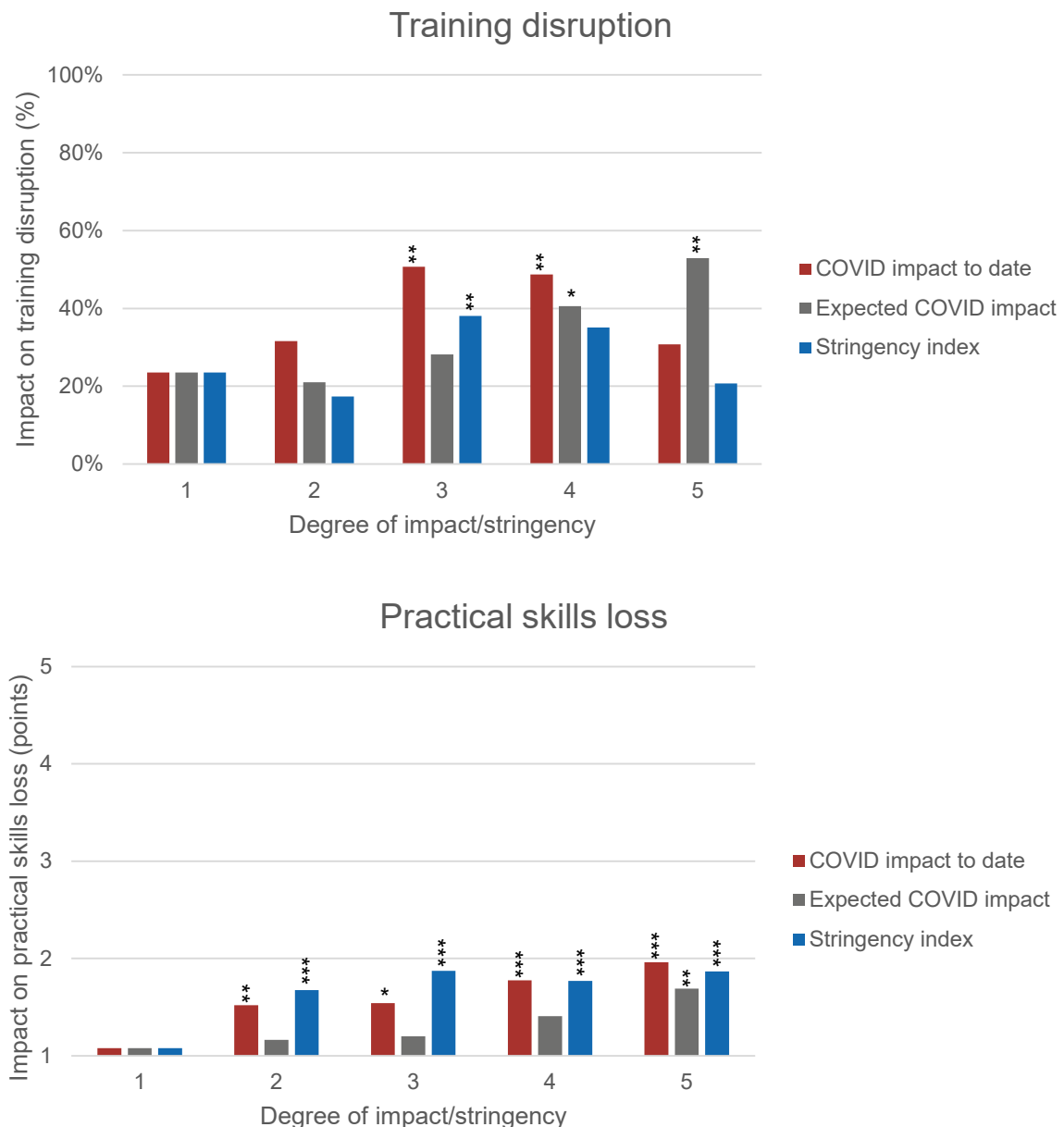
\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Note:

Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

Figure 3 shows the effects size on the vertical axis (effect added to constant) for all five levels of COVID impact to date (in red), expected future COVID impact (grey), and COVID stringency (blue). Higher bars indicate larger effects, so a higher percentage of training programs were disrupted and participants lost more practical skills. The scale for training disruption is the percentage of programs that were disrupted by the pandemic, and the scale for skills loss is a 1-5-point scale where 1 is no effect and 5 is a severe effect. Asterisks indicate statistical significance levels.

Figure 3: Program disruption and trainee practical skill loss by COVID-19 impact (categorical)



As expected, the effects of COVID-19 on training disruption and skills loss are not linear. The baseline level of program disruption is just above 20%, and for employers that had been impacted moderately and severely by COVID-19 (3 and 4 on the scale), disruption rates are closer to 50%. However, employers reporting very severe impact due to the pandemic do not have significantly more training disruption than the baseline. This could be due to survivorship bias—this survey went out to employers after a year

of pandemic conditions, so the very severely impacted employers may not have existed to respond—or an effect where these severely affected companies were given more support.

A similar pattern holds for COVID stringency—employers in moderately stringent states saw significantly more disruption to training programs, while those in very stringent and extremely stringent states are not significantly affected. Increased regulatory stringency could have come with increased support. Finally the effects on training disruption are essentially linear when we look at employers’ expectations for future COVID-19 impact. Greater expected impact leads to greater disruption, with employers expecting very severe and extremely severe future impact seeing much more disruption. If employers doubt their future survival, they are less likely to prioritize their skills development pipelines.

Although the impact of COVID-19 on training program disruption is non-linear, the pattern for participants’ skills development is much more linear. More impact of COVID-19, expected impact, and stringency are all associated stronger skill loss effects, although the overall level is very mild. Both COVID impact to date and COVID-related regulatory stringency significantly and increasingly affect skills loss at every level above the baseline. Expected future impact is only significant in the extreme. This indicates that, although employers may have been motivated to maintain training or could have received support to keep their programs going, the learning conditions imposed by the pandemic still made it harder for participants to learn practical skills.

### 3.4 COVID-19 Changes in Training

In the previous section, we found that COVID-19 did not necessarily cause employers to cancel their training programs but did still impact trainees’ learning. Therefore, we expect that there must have been some changes in how training was delivered during the pandemic. We asked employers about five possible modes of training during the COVID-19 pandemic. Respondents chose all options that applied at any point from spring 2020 to spring 2021:

1. Normal on-site work
2. Limited on-site work
3. Remote work
4. Training “homework” (not productive)
5. No practical training

Table 12 shows which training changes were driven by the pandemic and how they varied according to our explanatory variables. Only normal on-site work and limited on-site work are significant in both models, and no practical training is significant in M2. Remote work and training homework are not significant, indicating that these are not important training modes in the baseline specification.

Normal on-site work is by far the most common situation. It is less common for PD and internships, and more common for apprenticeships and OTJ training. All variation by sector and size disappears when we add additional variables in M2, but it appears this modality is less common in services and health and education than it is in agriculture or the baseline (mining, utilities, trade, and logistics). There are no differences depending on program age group or demographics. This mode does not consistently vary by COVID-19 impact or future impact, although employers in less-stringent states appear to maintain normal on-site training more often.

Limited on-site work is the second-most common training modality in the baseline specification. This mode is less common for interns, but similar for all other training types. It appears to be more common in large employers (M2 only). There are no differences by industry, although more-male employers are less likely to use limited on-site work. Employers that have been impacted more by the pandemic are more likely to take this approach.

Table 12: Training changes due to COVID-19

	<i>Dependent variable:</i>									
	Normal on-site work		Limited on-site work		Remote work		Training homework		No practical training	
	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	0.893*** (0.096)	0.954*** (0.147)	0.240*** (0.089)	0.262* (0.136)	-0.164 (0.113)	-0.107 (0.142)	-0.032 (0.031)	-0.083 (0.114)	-0.039 (0.045)	-0.218*** (0.084)
Apprenticeship	0.015 (0.034)	-0.009 (0.040)	-0.017 (0.031)	-0.037 (0.037)	0.044 (0.031)	0.066* (0.036)	0.015 (0.017)	0.015 (0.019)	-0.010 (0.021)	-0.017 (0.027)
Professional development	-0.306*** (0.036)	-0.281*** (0.044)	-0.018 (0.033)	-0.058 (0.040)	0.284*** (0.033)	0.265*** (0.039)	-0.004 (0.018)	0.009 (0.020)	0.045** (0.023)	0.062** (0.030)
Internship	-0.281*** (0.038)	-0.255*** (0.046)	-0.060* (0.034)	-0.089** (0.042)	0.094*** (0.035)	0.092** (0.041)	-0.032* (0.019)	-0.044** (0.021)	0.115*** (0.024)	0.109*** (0.031)
Nonprofit sector	-0.149*** (0.046)	-0.054 (0.059)	0.030 (0.041)	-0.007 (0.054)	0.209*** (0.042)	0.168*** (0.053)	0.090*** (0.022)	0.062** (0.028)	0.055* (0.028)	0.026 (0.039)
Private sector	0.082*** (0.031)	0.043 (0.041)	-0.048* (0.028)	-0.061 (0.037)	-0.025 (0.029)	0.041 (0.037)	0.016 (0.015)	0.016 (0.019)	0.012 (0.019)	0.015 (0.027)
Medium size	0.088*** (0.032)	0.055 (0.038)	-0.041 (0.029)	-0.039 (0.034)	-0.010 (0.029)	0.009 (0.034)	-0.043*** (0.016)	-0.046*** (0.018)	-0.052*** (0.020)	-0.057** (0.025)
Large size	-0.008 (0.034)	0.007 (0.044)	0.005 (0.031)	0.069* (0.040)	0.099*** (0.032)	0.145*** (0.040)	-0.004 (0.016)	0.012 (0.021)	-0.058*** (0.021)	-0.061** (0.029)
Trains youth	0.010 (0.030)	0.053 (0.036)	-0.022 (0.027)	-0.045 (0.033)	0.039 (0.028)	0.018 (0.032)	-0.020 (0.015)	0.011 (0.017)	-0.009 (0.019)	0.008 (0.024)
Agriculture		-0.027 (0.118)		-0.013 (0.108)		-0.026 (0.107)		0.024 (0.059)		-0.035 (0.077)
Services		-0.193*** (0.067)		-0.022 (0.061)		0.176*** (0.060)		0.017 (0.031)		0.049 (0.044)
Health and education		-0.219*** (0.079)		-0.056 (0.072)		0.141** (0.071)		0.021 (0.037)		0.100* (0.053)
Manufacturing and construction		0.016 (0.058)		0.012 (0.053)		-0.081 (0.052)		0.017 (0.027)		0.023 (0.039)
Program demographic		-0.039 (0.058)		-0.063 (0.052)		0.110** (0.051)		0.163*** (0.027)		0.028 (0.038)
Employer white		-0.008 (0.007)		0.009 (0.007)		-0.007 (0.007)		0.005 (0.004)		0.006 (0.005)
Employer male		-0.003 (0.008)		-0.014* (0.008)		0.011 (0.008)		0.0005 (0.004)		0.009 (0.006)
Impact of COVID-19	-0.048*** (0.016)	-0.014 (0.020)	0.033** (0.014)	0.038** (0.018)	0.012 (0.015)	-0.011 (0.018)	0.010 (0.008)	0.011 (0.009)	0.024** (0.010)	0.025* (0.013)
Expected future impact of COVID-19	-0.007 (0.017)	-0.015 (0.022)	-0.009 (0.016)	-0.024 (0.020)	0.013 (0.016)	0.029 (0.019)	0.009 (0.008)	0.009 (0.010)	0.006 (0.011)	0.007 (0.014)
COVID stringency index	-0.044* (0.023)	-0.045* (0.027)	-0.012 (0.022)	0.015 (0.026)	0.078*** (0.029)	0.036 (0.029)	0.011* (0.006)	0.003 (0.029)	0.005 (0.010)	0.019 (0.012)
Observations	1,015	685	1,015	685	1,015	685	1,015	685	1,015	685
Log Likelihood	-562.973	-383.925	-455.746	-321.508	-472.879	-309.039	-149.641	-116.042	-89.419	-118.050
Akaike Inf. Crit.	1,155.947	813.850	941.491	689.016	975.758	664.077	-269.281	-186.085	208.839	282.099
Bayesian Inf. Crit.	1,229.786	918.026	1,015.331	793.192	1,049.597	768.254	-195.441	-81.908	282.679	386.276

Note:

Note:

Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Remote work and training homework are both insignificant, but there is some significant variation. PD programs and internships are both more likely to switch to remote work, as are the non-profit sector and large employers. Employers in the services and health and education sectors are also more likely to use remote work for training. There is no consistent impact of program age group, but programs different from their host employers are more likely to be remote. COVID stringency may increase remote work for training very slightly (M2 only). Training homework is unproductive exercises related to practical skills. It is potentially more common in PD and internship programs, but both are not very stable across regressions. Homework is less common in medium employers, and does not vary by employer demographics, industry, or COVID impact. However, homework is more common when the training program is demographically different from the employer.

Finally, dropping practical training entirely is significantly infrequent with a negative constant. It is more common for internships and in the non-profit sector, and less common in large-sized employers and those that train youth. It is also more common among employers who were hit hard by COVID-19.

### 3.5 COVID-19 and Incentives to Train

The COVID-19 pandemic disrupted the labor market, with unemployment peaking at 14.8% in April of 2020<sup>14</sup>. This flood of workers onto the labor market could potentially have changed employers' access to skills. We asked employers to report how the availability of qualified/skilled workers changed since before the pandemic, generating the following three outcomes:

1. No change in the availability of qualified/skilled workers
2. Harder to find qualified/skilled workers
3. Easier to find qualified/skilled workers

Table 13 shows how employer characteristics, training behavior, demographics, industry, and COVID-19 impact affect employers' overall opinion of whether a lack of skills affects their growth, as well as how skills availability has changed since before the pandemic. As described earlier, most employers experience a lack of skilled or qualified workers limiting their growth. This is especially true for private-sector employers, larger and medium employers, those in the manufacturing and construction industries, and employers that are more white. Employers that have already been hit harder by COVID-19 report this problem slightly less, but those who expect larger future effects report it slightly more often.

<sup>14</sup> Federation of American Scientists. (2021). Unemployment Rates During the COVID-19 Pandemic. <https://fas.org/sgp/crs/misc/R46554.pdf>



Table 13: COVID-19 changes in availability of skilled workers

	Dependent variable:							
	Lack of skills affects growth		No change since pandemic		Worsened since pandemic		Improved since pandemic	
	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)	(M1)	(M2)
Constant	0.761*** (0.110)	0.590*** (0.153)	0.732*** (0.150)	0.474** (0.196)	0.217* (0.121)	0.539*** (0.167)	0.088 (0.118)	-0.032 (0.116)
Apprenticeship	0.014 (0.026)	0.014 (0.029)	-0.010 (0.040)	-0.030 (0.047)	-0.012 (0.041)	0.009 (0.047)	0.022 (0.020)	0.020 (0.022)
Professional development	-0.036 (0.028)	-0.016 (0.032)	-0.010 (0.042)	-0.048 (0.052)	-0.038 (0.043)	-0.009 (0.052)	0.043** (0.022)	0.055** (0.024)
Internship	0.024 (0.029)	0.024 (0.034)	-0.065 (0.045)	-0.036 (0.054)	0.022 (0.045)	0.022 (0.054)	0.046** (0.023)	0.012 (0.025)
Nonprofit sector	-0.029 (0.036)	-0.022 (0.044)	0.069 (0.054)	0.166** (0.070)	-0.049 (0.054)	-0.150** (0.070)	-0.046* (0.028)	-0.018 (0.033)
Private sector	0.094*** (0.024)	0.060** (0.031)	-0.034 (0.037)	-0.030 (0.048)	-0.001 (0.037)	-0.017 (0.048)	0.020 (0.019)	0.041* (0.022)
Medium size	0.047* (0.025)	0.058** (0.028)	-0.044 (0.038)	0.029 (0.044)	0.024 (0.038)	-0.009 (0.044)	0.006 (0.019)	-0.023 (0.020)
Large size	0.078*** (0.027)	0.067** (0.033)	-0.070* (0.041)	0.012 (0.053)	0.007 (0.041)	0.002 (0.052)	0.042** (0.021)	-0.003 (0.024)
Trains youth	-0.034 (0.023)	-0.023 (0.027)	0.026 (0.036)	-0.035 (0.042)	-0.025 (0.036)	0.028 (0.042)	-0.006 (0.018)	0.010 (0.019)
Agriculture		0.146 (0.092)		0.226 (0.142)		-0.184 (0.139)		-0.042 (0.067)
Services		0.065 (0.049)		0.100 (0.079)		-0.088 (0.078)		-0.003 (0.036)
Health and education		0.004 (0.058)		-0.060 (0.093)		0.065 (0.093)		0.005 (0.043)
Manufacturing and construction		0.099** (0.043)		-0.158** (0.068)		0.203*** (0.068)		-0.036 (0.031)
Program demographic		-0.049 (0.043)		0.021 (0.068)		-0.169** (0.068)		0.150*** (0.031)
Employer white		0.017*** (0.006)		0.00000 (0.009)		-0.012 (0.009)		0.013*** (0.004)
Employer male		-0.009 (0.006)		0.045*** (0.010)		-0.043*** (0.010)		-0.001 (0.005)
Impact of COVID-19	-0.029** (0.012)	-0.025* (0.015)	-0.057*** (0.019)	-0.070*** (0.024)	0.028 (0.019)	0.053** (0.023)	0.018* (0.010)	0.018* (0.011)
Expected future impact of COVID-19	0.047*** (0.013)	0.040** (0.016)	-0.020 (0.020)	-0.003 (0.026)	0.043** (0.020)	0.025 (0.025)	-0.011 (0.010)	-0.022* (0.012)
COVID stringency index	-0.004 (0.029)	0.010 (0.036)	0.009 (0.039)	0.027 (0.041)	-0.004 (0.030)	-0.023 (0.030)	-0.005 (0.033)	-0.005 (0.028)
Observations	1,008	685	1,015	685	1,015	685	1,015	685
Log Likelihood	-298.627	-184.341	-725.338	-492.624	-735.341	-492.650	-63.013	21.333
Akaike Inf. Crit.	627.254	414.681	1,480.676	1,031.247	1,500.682	1,031.300	156.026	3.334
Bayesian Inf. Crit.	700.990	518.858	1,554.516	1,135.424	1,574.522	1,135.476	229.865	107.511

Note:

Note:

Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

The other three outcomes in Table 13 describe how the availability of skilled and qualified employees has changed since the start of the pandemic. The effects are significant for no change and for a worsening, but not for improvement. Employers who were less affected by the COVID-19 pandemic are more often the ones seeing no change. More-male employers see no change more often, and those in the manufacturing and construction industries report no change less often. Weak evidence (M2 only) suggests that the non-profit sector may also report no change more often.

Many employers report that the mismatch between skills supply and demand has worsened since the start of the pandemic. Those in the manufacturing and construction industries report this problem more often. In contrast, employers with more women and those offering training programs different from their own demographics report skills-gap worsening less often. Weak evidence (M2 only) suggests that effects are stronger for employers more affected by COVID-19 and weaker in the non-profit sector. There is no effect of COVID stringency on the skills mismatch in any model.



## 4 Limitations

The limitations of this study can chiefly be divided into, on one hand, the representativeness and interpretation of the data, and on the other, the quality of the data itself. Both cases call for caution when drawing conclusion from the findings.

Concerning the first, it is critical to bear in mind that the data collected in this study is not representative either of US companies overall, or companies that train specifically. Rather, the survey and analyses are designed to explore the dynamics of training and the impact of the COVID-19 pandemic within companies who are part of the PAYA and CareerWise networks. The results provide useful information on trends within companies that train and how training programs may have been affected by COVID, which may be used as a benchmark for better understanding the training landscape. However, the results should not be generalized to the US training landscape overall, as they relate only to the specific places, industries and programs surveyed.

A further point to bear in mind when interpreting the results is the timing of the survey. In the field in early 2021, a year into the pandemic, the possibility that the results are affected by “survivorship bias” cannot be excluded. In other words, companies that have survived up to this time may have different characteristics to those which have closed. Moreover, we cannot assess the impact of employer closure on training, nor how many people in training may no longer be due to the closure of a firm.

One final point on interpretation on results concerns the selection of analytical models. We have opted for simplicity and ease of interpretation over complexity. This means that the analytical models in this paper are all linear regression models with basic linear control variables and no cross-variable interactions. This means that results can be interpreted simply (as percentage point changes or changes on a 5-point scale), but also that we may not capture all effects with complete precision. However, the stability of results across models nevertheless suggests that the specification selected is appropriate for the analyses. While it may have been possible to approximate representativeness through weighting, we are not confident enough in the robustness of the dataset to have chosen this approach.

The variables in the analyses themselves also call for some level of caution in interpretation. Demographic variables, particularly pertaining to gender and race, are sensitive and prone to both non-response and social desirability bias. We also chose to analyze whether or not program demographics vary from employer demographics overall without further asking in what way the demographics do in fact differ. However, we can assume with reasonable certainty that given the companies who answer the survey tend towards a high proportion of white, male employees, that training programs that are “different” from the employer are in fact more diverse. Finally, the standard cautions with self-reported data apply – we cannot be certain that respondents correctly report their program types in particular, which may bias some of the findings concerning type of program, but this caveat also extends to almost all variables in the analysis.

## 5 Conclusions

Employers provide training mainly because they need skilled workers. Potential employees with the right skills and/or qualifications are hard to find, enough so that employers report the mismatch in skills supply and demand limits their growth. Job-related practical skills, problem-solving skills, and soft skills are all particularly in demand. Employers hire from within most often, but training is a crucial path to the right skills and is a strategy employers use just as much as they hire from four-year colleges and universities.

Employers also train for social motivations, and they tend to focus on different populations when they do. Evidence indicates that the employers who train to improve their own diversity and to move towards skills-based hiring tend to have more diverse training programs. Of course, training programs more diverse than the employer are also a very useful method of getting skilled workers. Employers who need skills not taught in the education system and employers who use training as a trial period for new workers both tend to have more diverse training programs. Employers who want to support their local communities and keep existing employees engaged often operate youth training programs.

Different types of training take different forms and might be expected to have different purposes. However, the evidence does not support that idea—employers do not consistently use specific training types to achieve different goals. In contrast, there are some major differences across training type from the participant perspective. Although apprenticeships and PD offer high value for participants in the form of portable or at least internal credit and qualifications, internships and OTJ training offer little more than experience. Similarly, apprenticeships offer multiple assurances of quality for participants while OTJ training and internships generally do not. PD falls somewhere in the middle. In addition, many apprenticeships are registered as an additional form of value and a structure that requires a certain level of quality.

The COVID-19 pandemic was a major shock to almost every facet of American society, including the labor market and employers' training programs. Interestingly, employers' expectations for how much the pandemic will affect them in 2021 and 2022 matters just as much as how much it has already affected them, while the stringency of regulations related to the pandemic generally does not. From a training perspective, expectations of disruption can be just as damaging as the problems employers already face.

The shock of COVID-19 identified the more and less vulnerable training programs, employers, and individuals. Only internships were significantly disrupted, but participants in all training programs experienced some learning loss. The worst-hit were those in PD and internship programs, while apprenticeship and OTJ training programs were less affected.

Training methods in apprenticeships and OTJ training were also the least likely to be impacted by the pandemic, with trainees still mostly able to work on-site at some point over the first year of the pandemic—even controlling for industry. Apprentices did potentially have a small increase in remote work, but PD and internships were much less likely to get on-site at any point during the pandemic and much more likely to work remotely or get no training at all. Interns were also less likely to get any limited on-site experience at any point during the pandemic. Apprenticeship—even under employers' self-definition and not limited to Registered Apprenticeship—offers the most value, ensures training quality, and is among the most robust and resilient training models.

These differences in the value, quality, and robustness of training programs are especially important because the different training types often serve different groups. Apprenticeship—the most valuable and high-quality program—typically targets youth and young adults. PD is next for value and quality, but typically does not target youth and generally serves a population that matches the host employer’s race and gender distributions—mainly because PD serves existing employees. OTJ training is massively common but does not always provide transferable value or include assurances that trainees will learn what they need. Finally, internships target youth but provide very little consistently portable value except experience and often lack characteristics that could ensure training quality.

The COVID-19 pandemic seems to have affected different groups of training participants differently. Training programs targeting youth are of slightly worse value and quality, but young people in training were not more likely to have training disrupted or experience skills loss. In contrast, although participants in programs more diverse than their host employers get essentially equivalent value and quality out of their training programs, their training was disrupted more frequently by COVID-19. They were also more likely to do remote work or unproductive homework at some point during the pandemic.

For employers, broadening the pool of potential workers and offering training to them seems to help employers get the skills they need, thus fueling growth and recovery. For individuals, high-value, high-quality training programs are a path to learning employable skills. Apprenticeships especially offer high value and high quality for participants, and seem to be more robust to major economic shocks like the COVID-19 pandemic.

# Appendix

Table 14: Effect of COVID-19 on training, impact and future impact as categorical variables

	<i>Dependent variable:</i>			
	Disruption to training		Effects on practical training	
	(M1)	(M2)	(M1)	(M2)
Constant	0.204* (0.113)	0.235 (0.151)	1.338*** (0.237)	1.077*** (0.383)
Apprenticeship	0.069* (0.040)	0.045 (0.047)	0.085 (0.097)	0.124 (0.114)
Professional development	0.080* (0.042)	0.090* (0.052)	0.281*** (0.104)	0.311** (0.125)
Internship	0.152*** (0.044)	0.156*** (0.054)	0.503*** (0.110)	0.389*** (0.131)
Nonprofit sector	-0.005 (0.053)	-0.035 (0.068)	0.274** (0.131)	0.016 (0.169)
Private sector	-0.073** (0.037)	-0.134*** (0.048)	-0.191** (0.090)	-0.207* (0.117)
Medium size	-0.013 (0.037)	-0.015 (0.044)	-0.087 (0.093)	-0.088 (0.108)
Large size	-0.035 (0.040)	0.098* (0.051)	-0.006 (0.097)	0.171 (0.123)
Trains youth	-0.039 (0.035)	-0.027 (0.042)	0.039 (0.086)	0.064 (0.102)
Agriculture		0.012 (0.137)		-0.683** (0.332)
Services		-0.125 (0.077)		0.422** (0.189)
Health and education		-0.169* (0.093)		0.268 (0.227)
Manufacturing and construction		0.007 (0.068)		0.003 (0.165)
Program demographic		0.100 (0.068)		0.239 (0.165)
Employer white		0.005 (0.008)		0.011 (0.020)
Employer male		-0.006 (0.010)		0.005 (0.024)
COVID impact 2/5	0.077 (0.080)	0.081 (0.090)	0.421** (0.195)	0.444** (0.217)
COVID impact 3/5	0.176* (0.091)	0.272** (0.107)	0.518** (0.222)	0.463* (0.259)
COVID impact 4/5	0.208** (0.093)	0.252** (0.108)	0.842*** (0.226)	0.698*** (0.261)
COVID impact 5/5	0.068 (0.099)	0.073 (0.121)	1.057*** (0.243)	0.884*** (0.293)
Expected future COVID impact 2/5	0.017 (0.059)	-0.025 (0.070)	0.185 (0.145)	0.087 (0.170)
Expected future COVID impact 3/5	0.062 (0.069)	0.047 (0.083)	0.171 (0.168)	0.124 (0.202)
Expected future COVID impact 4/5	0.215*** (0.073)	0.171* (0.088)	0.217 (0.180)	0.329 (0.215)
Expected future COVID impact 5/5	0.164* (0.095)	0.294** (0.125)	0.472** (0.234)	0.612** (0.303)
COVID stringency index 2/5	0.080 (0.117)	-0.061 (0.062)	0.312 (0.218)	0.597*** (0.208)
COVID stringency index 3/5	0.101 (0.116)	0.146** (0.074)	0.561** (0.225)	0.797*** (0.222)
COVID stringency index 4/5	0.003 (0.117)	0.116 (0.090)	0.415* (0.232)	0.693*** (0.244)
COVID stringency index 5/5	-0.023 (0.108)	-0.028 (0.062)	0.773*** (0.200)	0.791*** (0.193)
Observations	1,015	685	987	671
Log Likelihood	-715.178	-492.867	-1,552.436	-1,042.522
Akaike Inf. Crit.	1,478.356	1,049.734	3,152.871	2,149.045
Bayesian Inf. Crit.	1,596.500	1,194.676	3,270.343	2,293.326

Note:

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01  
Reference categories: OTJ training program type, public sector, small size, does not train youth, industry: mining utilities trade and logistics, program demographic matches employer. Employer whiteness and maleness increase in intervals of 10 percentage points.

## Author Information

Caves Katherine, Dr.  
Chair of Education Systems, ETH Zurich  
Leonhardstrasse 21  
8092 Zürich  
[katie.caves@mtec.ethz.ch](mailto:katie.caves@mtec.ethz.ch)

McDonald Patrick, Dr.  
Chair of Education Systems, ETH Zurich  
Leonhardstrasse 21  
8092 Zürich  
[patrick.mcdonald@mtec.ethz.ch](mailto:patrick.mcdonald@mtec.ethz.ch)

## Contact

ETH Zürich  
Chair of Education Systems  
Leonhardstrasse 21  
8092 Zürich

[www.ces.ethz.ch](http://www.ces.ethz.ch) →

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