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Working from home is here to stay, but how does it affect workplace learning?

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Abstract

This paper analyses how working from home affects workplace learning in terms of theoretical and practical knowledge during COVID19. We employ panel data gathered in monthly surveys of respondents in training companies between October 2020 and March 2022 to investigate this question. Apprentices in Switzerland are our case study. We address potential endogeneity concerns in two ways. First, we exploit variation across survey respondents and time in two-way fixed effects models. Second, we pursue an instrumental variable "shift-share"-type approach that leverages how occupations react to exogenous changes in working from home regulations. The results suggest that working from home has a significantly negative impact on practical knowledge but not theoretical knowledge, relative to frequenting the workplace. We do not find significant heterogeneity across company size. Similarly, our results do not vary significantly between occupations in which working from home is relatively more or less prevalent. Our findings remain robust to a wide range of robustness checks. Our evidence-based recommendations aim to preserve the acquisition of knowledge through workplace training.

Keywords Workplace learning, Working from home, Human capital, Shift-share instrumental variable estimation, Two-way fixed effects

JEL Classification I20, I21, I23

1 Introduction

Companies' organisational paradigms and working modes were heavily affected by COVID19 response measures. Working from home, sometimes referred to as remote working or teleworking, has become widespread and is here to stay (Bloom et al., 2023; Gibbs et al., 2023). This change affects workplace learning by impeding interpersonal contact. It also challenges existing methods of knowledge acquisition through a shift to remote settings (Gibbs et al., 2023; Yang et al., 2022). Therefore, it is fundamental to investigate how working from home affects workplace learning (Eraut, 2007). In Switzerland, the majority of upper secondary education students pursue dual programmes. Dual programmes combine learning in the workplace and through classroom instruction. Therefore, we use dual programmes in Switzerland as case study to explore how working from home affects workplace learning in terms of practical and theoretical knowledge.

We postulate that working from home affects workplace learning through three channels and mechanisms. First, working from home reduces in-person interactions (e.g. Gibbs et al., 2023; Yang et al., 2022). Infrequent in-person interactions entail less informal learning through interactions with mentors and trainers, with a direct effect on apprentices' workplace learning (Billett, 2001, 2014; Eraut, 2007; Nielsen, 2010). Second, working from home might hamper workplace learning by affecting stress, health and well-being (see, e.g., Kuenn et al., 2022; Straus et al., 2022; Salamon et al., 2021). Empirical evidence shows that distance instruction affects students' well-being (Duckworth et al., 2021; Giusti et al., 2021).

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Third, a lack of infrastructure, particularly digital infrastructure, might hamper workplace learning (ILO, 2021; OECD, 2020b).

This paper's original contribution is to assess the impact of working from home on workplace learning relative to frequenting the workplace. We further differentiate between theoretical and practical knowledge. Albeit knowledge acquisition differs between classroom instruction and workplace, distance instruction also depends on remote communication and technological capabilities. Therefore, we complement the literature on the impact of distance instruction on knowledge acquisition in high schools, community colleges and universities. This literature suggests that distance instruction hampers acquisition of mostly theoretical knowledge for community colleges (see, e.g., Xu & Jaggars, 2013; Mohammadian et al., 2021) and universities (see, e.g., Alpert et al., 2016; Bettinger et al., 2017; Joyce et al., 2015). The literature on the impact of school closures during COVID19 suggests that distance instruction decreased theoretical knowledge for high school students (see, e.g., Agostinelli et al., 2022; Moliner et al., 2022).

Working from home affects both theoretical and practical knowledge, but much less is known regarding the effect of distance instruction on practical knowledge. Descriptive evidence suggests that the shift to distance instruction and closures of training workplaces during COVID19 decreased practical knowledge acquisition (ILO, 2021; OECD, 2020a). Zaghal et al. (2022) do not find a significant effect of distance instruction on practical knowledge. Even less papers differentiate between practical and theoretical knowledge. Soltanimehr et al. (2019) find that distance instruction improves theoretical knowledge but has no effect on practical knowledge. Conversely, Heitmann et al. (2022) distance instruction increases practical knowledge but decreases theoretical knowledge.

Apart from the descriptive evidence of ILO (2021) and OECD (2020a), the literature on knowledge acquisition analyses focuses on the effect of distance instruction rather than working from home. Therefore, we further build on the literature analysing the effect of working from home on worker productivity. The literature review of Hackney et al. (2022) finds that non-mandatory working from home increases productivity (see, e.g., Bloom et al., 2015). However, the literature tends to find negative effects of mandatory working from home on productivity, e.g. during COVID19 (Atkin et al., 2023; Emanuel & Harrington, 2023; Etheridge et al., 2020; Gibbs et al., 2023; Kitagawa et al., 2021; Morikawa, 2022; Yang et al., 2022). These productivity losses are lower for workers in industries or occupations in which working from home was already prevalent before COVID19 (Bartik et al., 2020; Etheridge et al., 2020; Morikawa, 2022).

We contribute to this literature by analysing knowledge acquisition as a mechanism through which working from home affects productivity. To the best of our knowledge, no published study evaluates the effect of working from home on both practical and theoretical knowledge. This paper seeks to fill this gap in the literature. We employ two identification strategies to estimate these effects. First, a two-way fixed effects model leverages respondent and time-varying variation. Second, an instrumental variable approach exploits the reaction of occupations to changes in federal regulation making working from home recommended or compulsory wherever possible. The instrument is of a "shift-share" nature. Instrumental variable results are driven by occupational responses to changes in federal policy regimes regarding working from home. They consequently do not identify the identical effect as OLS baseline two-way fixed effects regressions do.

We use monthly and bimonthly data from the Apprenticeship Pulse project between October 2020 and March 2022. Online surveys were filled out by apprentice-trainers, CEOs, founders, and HR staff in training companies. Most respondents have highly regular, direct, and frequent contact with apprentices.

Our results demonstrate that working from home hampers workplace learning. However, although working from home reduces practical knowledge, it has no significant effect on theoretical knowledge. We do not find significant heterogeneity in the effect of working from home across company size and prevalence of working from home within occupations. Furthermore, our estimations are qualitatively robust to several robustness tests. Restricting the sample to apprentice-trainer respondents only, limiting the time elapsed between responses and accounting for multiple hypotheses testing all yield results qualitatively aligned with baseline results. Consequently, results bear implications for companies' strategies to safeguard and improve workers' knowledge through effective workplace training.

The rest of the paper is structured as follows. Section 2 describes the VET system and COVID19-related regulations in Switzerland. Section 3 devises our hypotheses based on literature on the effect of COVID19 on practical and theoretical knowledge. Section 4 shows our data and survey methodology. Section 5 presents our econometric analysis. Section 6 discusses our results and robustness checks, and Sect. 7 concludes, discusses study limitations and presents policy recommendations.

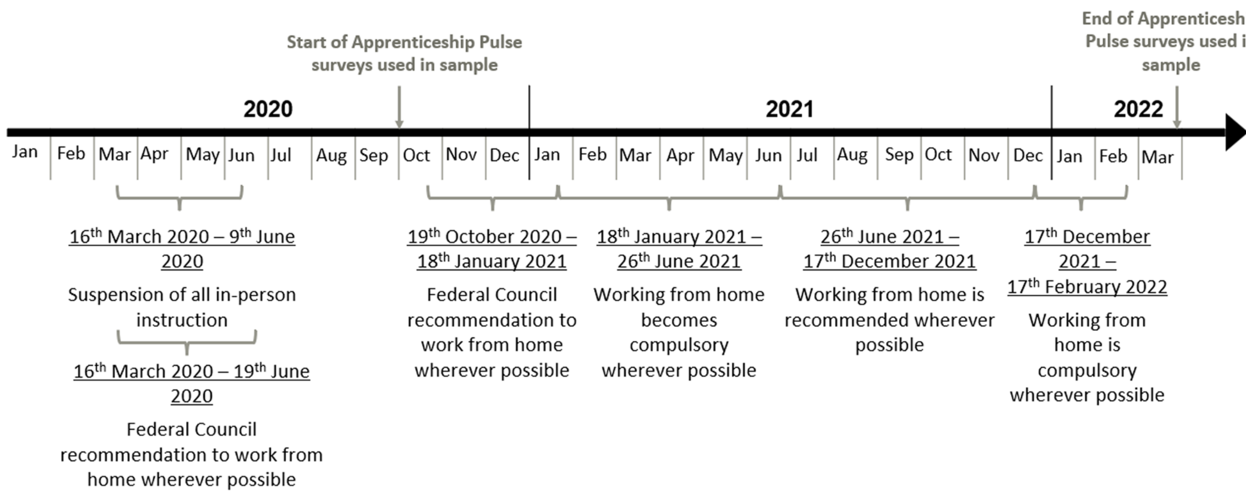

Fig. 1 Timeline of federal regulation of working from home and school closures. *Notes*: The figure shows the development of federal regulation regarding working from home and school closures, i.e. suspension of in-person instruction in schools. Working from home was only recommended or compulsory wherever possible. Sources: Own illustration, Federal Council (2020a, 2020b, 2022), Federal Office for Public Health (2022)

2 Context

2.1 Dual VET in Switzerland

Dual VET in Switzerland merges workplace learning and classroom education. Apprentices typically spend 60–80% of their time in the workplace, which is supplemented by 20–40% of their time spent in VET schools. VET programmes last between two to four years and train youth towards one of 253 occupations (State Secretariat for Education, Research and Innovation, SERI, 2021). Completion of the two-year programme yields a Federal Certificate of Vocational Education and Training. The three-to-four-year training grants the Federal Diploma Vocational Education and Training. This diploma gives conditional access to higher vocational training and the professional baccalaureate. 66% of students in Switzerland who leave compulsory education in Switzerland enrol in VET (SERI, 2021).

Swiss apprentices have high levels of responsibility and interact with clients in customer-facing roles (Muehlemann et al., 2010). This distinctive approach has strong implications for apprentices' workplace learning. Early on in their dual VET programme, apprentices face unexpected situations and must develop tacit and suitable knowledge to cope with their environment (Bolli & Hof, 2018). If apprentices frequent the workplace, they may develop capacities to overcome these challenges through mimicry of senior colleagues (Billett, 2014).

The well-established Swiss dual VET system presents an ideal setting to evaluate the transmission of practical and theoretical knowledge due to its dual nature. Apprentices frequent their respective workplaces *and* vocational schools. They therefore complement the acquisition of practical knowledge and "hands-on" experiential knowledge with relevant theoretical knowledge.

Furthermore, in Switzerland, close collaboration[1] occurs between all VET stakeholders (including employer associations, regional and national governments, educational institutions) in designing structured programme curricula and qualification standards (Renold et al., 2016). Curricula are subsequently regularly reviewed and updated to reflect the needs of training companies. Curricula updates ensure apprenticeship graduates possess the necessary competences to remain competitive on the labour market. Curricula are highly standardised. VET qualifications are recognised nationwide to guarantee harmonisation on a national level (Renold et al., 2016).

2.2 Regulation of working from home during COVID19

Switzerland's first confirmed COVID19 case was on the 25th of February 2020. After that, sanitary measures came into force successively from the end of February. All COVID19 response measures were lifted on the first of April 2022. Figure 1 shows the timeline of the most relevant COVID19 responses by the Swiss Federal Council for this paper. Figure 1 also indicates how our data from "Apprenticeship Pulse" surveys overlaps with these COVID19 response measures. The most relevant regulations include suspension of in-person instruction, recommendation to work from home and compulsory working

[1] This collaborative approach is referred to as "collective governance" (Graf et al., 2023). Collective governance relies on an associational logic between all dual VET stakeholders and aims to provide an increase in collective welfare (Culpepper, 2019). The state assumes the role of "enabling state" (Graf et al., 2023) and confers a central role to employer associations.

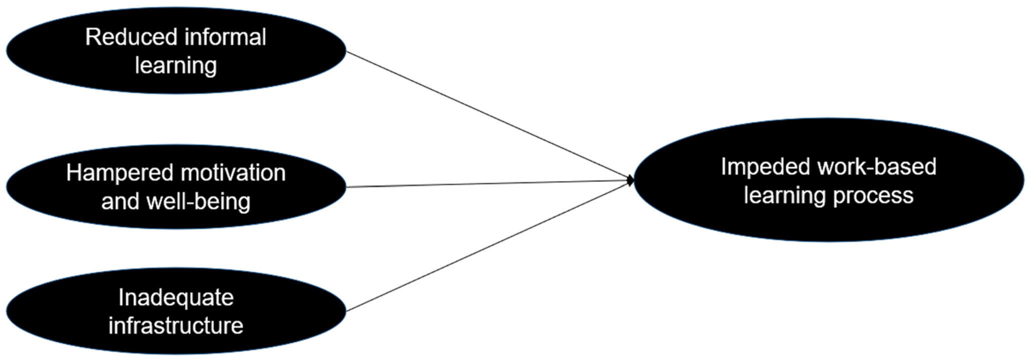

Fig. 2 Channels through which Working from Home Impacts Apprentices' Learning. Source: Authors' own elaboration

from home. Importantly, working from home was only recommended or compulsory wherever it was possible.

In-person instruction was suspended for less than three months and this period is not within our sample. Furthermore, working from home only became compulsory over a total of about seven months (roughly the first half of 2021, as well as the very end of 2021 and start of 2022). However, it was recommended for a total of approximately twelve months (mostly over the latter half of 2021). The collection of data used in this paper through the "Apprenticeship Pulse" project started in April 2020 as working from home was unregulated. Nonetheless, employers had the obligation to allow staff at especially high risk to work from home.[2] Data collection ended when no more federal guidelines were published regarding working from home.

3 Theoretical considerations

Working from home may have affected the workplace learning of apprentices through three channels shown in Fig. 2: (1) reduced informal learning, (2) hampered motivation and well-being and (3) inadequate infrastructure.

The first channel is that working from home may hinder informal learning. Working from home hinders in-person interactions with employees' respective hierarchy or colleagues (Gibbs et al., 2023). Yang et al. (2022) demonstrate that while working from home, interconnectedness within companies declined. This could reduce workplace learning of apprentices through lower connectivity and less information exchanges (Emanuel & Harrington, 2023). Emanuel et al. (2023) find that relative to working from home, physical proximity to coworkers in the office increases the amount of feedback received by mentees and distributed by mentors.

The second channel is that a lack of face-to-face interactions with colleagues and hierarchy hinders apprentices' motivation. Working from home entails the reception of less praise by apprentices delivered by their supervisors (ILO, 2021). This impairs motivation (Wei and Yaznifard, 2014) and affects mental well-being (Etheridge et al., 2020). In remote settings, the constant availability of support for professional tasks may lack. This may leave inexperienced workers overwhelmed (Emanuel & Harrington, 2023), eroding their motivation.

The third channel is that a lack of infrastructure affects apprentices' workplace learning. Kitagawa et al. (2021) find that productivity levels of on-site workers is higher than for workers working from home. They argue this is because inadequate working from home setups hamper effective communication. Further, apprentices and trainers may lack the digital knowledge to partake in online courses effectively (ILO, 2021; OECD, 2020b). Morikawa (2022) underlines that productivity losses were indeed exacerbated for all workers who were not already used to working from home pre-pandemic. Efficient and effective working from home necessitates familiarity with certain technologies and remote methods of communication. Consequently, considering extant literature, we formulate hypothesis H1[3]:

H1: Working from home impedes workplace learning relative to frequenting the workplace.

We further differentiate workplace learning in terms of practical and theoretical knowledge. Klausen and Petersen (2021) specify that theoretical knowledge is indirect and indifferent to subject matter. For knowledge to be defined as theoretical, the basis for knowledge must be testimony, inference, or a blend of both. We refer to practical knowledge as idiosyncratic, contextual,

[2] See https://www.admin.ch/gov/en/start/documentation/media-releases.msg-id-78818.html.

[3] It should be noted that mechanisms might exist through which working from home improves learning. Concretely, having less commuting time and lower infection risk might improve motivation of apprentices. Furthermore, fewer distractions from coworkers and less time spent in meetings could have potentially had a positive effect on learning outcomes (see, e.g. Chen et al., 2023).

tacit or experience-based guides to action (Thurlings & van Diggelen, 2021). See Verloop et al., 2001, and de Kleijn et al., 2015, for a further discussion of practical knowledge.

Results from the ILO (2021) survey indicate that apprentices' engagement was disproportionately more eroded for those pursuing programmes bearing a larger share of practical tasks. Indeed, amidst the COVID19 pandemic, stimulating activities usually conducted in laboratories or workshops were supplanted by "more passive methods of engaging with content" (ILO, 2021, p.14), such as reading or videoconferences. The ILO (2021) report further states that remote instruction was focused on theoretical knowledge. The impartment of practical knowledge was consequently neglected. Therefore, apprentices particularly interested in pursuing a practical activity were disproportionately demotivated. This leads us to formulate hypothesis H2:

H2: Working from home impedes the learning of practical knowledge more than the learning of theoretical knowledge.

Bellmann et al. (2021) show that large companies have invested more funds in working from home infrastructure than small and medium companies during COVID19. Rueckert et al. (2020) also find that larger companies are comparatively more digitally active. Apprentices in small companies might therefore have less access to relevant information and online training platforms. Motresor and Vezzani (2023) show that large companies are far ahead of small and medium companies regarding the adoption of digital technologies. We consequently formulate hypothesis H3:

H3: Working from home impedes workplace learning in large companies relatively less than it impedes workplace learning in small and medium size companies.

We further expect heterogeneity in the effect of working from home on workplace learning across occupations. Bellmann et al. (2021) find that 62% of companies in which working from home was feasible invested in digital technologies. On the other hand, only 31% of companies for whom working from home was unfeasible invested in digital technologies. Etheridge et al. (2020) report that on average, workers in occupations and industries characterised as less suitable for working from home reported larger productivity losses. Bartik et al. (2020) underline that working from home is much more prevalent in high paying industries. Workers tend to hold higher qualifications in these industries. The authors find that following the COVID19 pandemic, productivity had dropped by less in these industries. Morikawa (2022) finds that highly-educated and high wage individuals working from home experienced lower declines in productivity. These individuals are concentrated within a few industries and occupations in which working from home tends to be more prevalent. This leads us to hypothesis H4:

H4: Working from home impedes workplace learning relatively more in occupations in which working from home is less prevalent.

4 Data

4.1 Data source

Data from the Apprenticeship Pulse" project consists of online surveys among respondents across the 26 Swiss cantons and Liechtenstein. Most respondents are apprentice-trainers, CEOs, founders or human resources staff. We use monthly data from October 2020 to January 2021 and bimonthly data from March 2021 to March 2022. Survey responses are spread out across days within each month.

Each respondent indicates for which cantons and occupations they respond. Surveys do not indicate company-level data but respondent-level data. One single company may have several respondents supervising different apprentices. Multiple respondents may also answer for the same apprentice. A survey respondent may respond for multiple apprentices, active in distinct occupations. Amongst all survey respondents present in our estimation sample, around a third are apprentice-trainers.

The average (arithmetic mean) overall survey response rate over our sampled period is 5%. German-speaking cantons are consistently more represented than French and Italian speaking cantons in our sample. This occurs as the Yousty apprenticeship platform supplied the ETH Zurich with a sample of Swiss training companies from their database. The clients of this apprenticeship platform are training companies principally located in German-speaking Switzerland.[4] We also identify heterogeneity in representativeness across occupations. Occupations within the chemistry and physics occupation group are the most represented occupations throughout our analysis period. Sampled training companies in chemistry and physics represent on average 7% of the total population of training companies in Switzerland. Information Technology (IT) is the second most represented occupation. Sampled IT companies in this occupation representing on average 7% of the total population.

We employ probability weights, also referred to as sampling weights, in our regressions to reinforce the external validity of our results (population representativeness). To construct these weights, we source data pertaining to the Swiss population of apprentices and apprentice-training companies from the Federal Statistical Office's basic

[4] As at 2020, circa 73.8% of Swiss citizens lived in German-speaking or bilingual cantons (Statistique Geneve, 2021).

professional training statistics (Federal Statistical Office, 2021a). The probability weights we employ correspond to the inverse of the probability of being selected into our sample. This corresponds to the total number of apprentices in the population divided by the total number of apprentices reported in our sample. Cells containing the probability weights are month-, company size-, language region- and occupation group-specific. We discuss this further in Sect. 5.

4.2 Variable selection

We use two dependent variables. The first dependent variable, "Theoretical knowledge" denotes the effect of COVID19-induced changes to companies' activity on apprentices' theoretical knowledge. "Theoretical knowledge" is measured using a Likert scale ranging from -2 to 2. The value -2 means that "COVID19-induced changes have substantially worsened apprentices' theoretical knowledge". The value 2 represents the answer "COVID19-induced changes have greatly improved apprentices' theoretical knowledge". A value of 0 indicates COVID19-induced changes have not affected apprentices' theoretical knowledge. The second dependent variable, "Practical knowledge", denotes the effect of COVID19-induced changes to the companies' activity on apprentices' practical knowledge. Its scale of measurement is a Likert scale ranging from − 2 to 2 as for "Theoretical knowledge".

Both "Practical knowledge" and "Theoretical knowledge" variables were first measured at the start of the second COVID19 wave in October 2020. They were measured monthly until January 2021 and subsequently every two months until March 2022. This grants us a total of 11 time periods, which are not all consecutive. In October 2020, "Practical knowledge" and "Theoretical knowledge" were asked for each occupation separately. These occupation-specific values are aggregated as occupation-specific weighted averages, weighted by the number of apprentices reported by respondents.

In all survey months, we asked respondents to report apprentices' working activities separately for each occupation. The regressor of interest is working from home. This variable is the occupation-weighted apprentice share of respondent i who are working from home in month t. Occupation-weighted signifies that it is weighted by the number of apprentices working in this occupation. We control for the occupation-weighted apprentice share of two other alternative activities. "Homework" indicates whether companies have issued homework to their apprentices. "NoFirmTraining" captures a situation in which apprentices receive no company-provided training at all. The base group thus comprises apprentices frequenting the workplace.

The five remaining regressors control for the situations of the respondents' respective companies. We control for the prevalence of short-time work, also referred to as *Kurzarbeit* ("Prevalence Short-Time Work"), the extent of sanitary protocol's effect ("Sanitary Protocol"), effect of financial distress ("Financial Distress"), threat of bankruptcy's effect ("Risk Bankruptcy"), and the extent of temporary closure's effect ("Temporary Closure") on company employees. These variables are interaction terms. A dummy variable, indicating whether the company's employees have been affected by these company situations, is multiplied by a Likert scale indicating the extent of the impact of COVID19 on company employees in general. These variables can assume any integer value between 0 and 5. 0 means the respondent's company was not affected by the measure in question. 5 means the company's employees were severely affected.

4.3 Descriptive statistics

Table 1 below presents descriptive statistics for our dependent variables and regressors. The (arithmetic) mean values of "Practical knowledge" and "Theoretical knowledge" across our estimation sample are -0.162 and -0.263, respectively. This indicates that on average survey respondents assert that COVID19-induced changes in companies' activity were deleterious to apprentices' practical and theoretical knowledge. These *unconditional* means highlight that on average, respondents believe COVID19 has had a more negative impact on theoretical rather than practical knowledge.

Our regressor of interest, "Work from home", has a mean value of 8.8% in our estimation sample. Most apprentices frequented their respective workplaces. This may seem counter-intuitive considering the federal working from home recommendations and obligations reviewed in Sect. 2.1. Nonetheless, the recommendation and obligation to work from home enacted by the Federal Council only targeted individuals occupying jobs permitting to work from home, and "high-risk" individuals (Federal Council, 2020a). Working from home tends to be less feasible in the construction and manufacturing industries (Dey et al., 2020). The prevalence of these industries in our data illustrates the low proportion of apprentices working from home despite federal measures.

Occupations in which working from home is more prevalent, in our sample, are constituted by information technology (IT) and administration. An average of, respectively, 37% and 17% of apprentices in IT and administration worked from home over the two years comprised in our sample classification. The classification of working from home prevalence we postulate is confirmed by the American Time Use Survey (Dey et al.,

Table 1 Descriptive statistics of variables

Variable	Mean	Standard deviation	Minimum	Maximum	Observations
Dependent variables					
Theoretical knowledge	−0.263	0.508	−2	2	11,411
Practical knowledge	−0.162	0.467	−2	2	11,450
Regressor of interest					
Work from home	0.088		0	1	11,450
Control variables					
Company-issued homework	0.014		0	1	11,450
No in-company training	0.006		0	1	11,450
Prevalence short-time Work	0.120	0.688	0	5	11,450
Sanitary protocol	2.677	1.489	0	5	11,450
Financial distress	0.143	0.737	0	5	11,450
Risk bankruptcy	0.019	0.286	0	5	11,450
Temporary closure	0.059	0.501	0	5	11,450
Subsample analysis					11,450
Medium and large companies	0.379		0	1	11,450
Occupation in which working from home is more prevalent	0.345		0	1	11,450

Descriptive statistics are presented for the estimation sample in the "Practical knowledge" specification

2020[5]). This survey stipulates that the two occupations where working from home was the most prevalent are IT and administration.

On average, 34.9% of survey respondents figuring in our estimation sample responded for apprentices pursuing programmes in the two aforementioned occupations. 38% of respondents declared that the apprentices they were responding for worked at companies employing at least 50 individuals (respectively "Occupation in which working from home is prevalent" and "Medium and Large companies" in Table 1 below). Therefore, most apprentices in our sample worked at companies with less than 50 employees. In parallel, most apprentices work in occupations in which working from home is less prevalent.

5 Empirical methodology

5.1 Baseline two-way fixed effects methodology

The baseline two-way fixed effects equations are as follows:

$$\begin{aligned} Practical\ Knowledge_{it} = &\alpha_i + \beta_1 WorkingfromHome_{it} \\ &+ \beta_2 X'_{it} + \gamma_{og} + \delta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} Theoretical\ Knowledge_{it} = &\alpha_i + \varphi_1 WorkingfromHome_{it} \\ &+ \varphi_2 X'_{it} + \gamma_{og} + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

β_1 and φ_1 are our coefficients of interest. They capture whether respondent i reported having apprentices working from home in month t. γ_{og} are occupation group fixed effects. δ_t represents month fixed effects. X'_{it} is a vector of time-varying control variables as shown in Table 1. Concretely, we control for whether apprentices receive homework or no company-provided training. X'_{it} also contains the number of apprentices reported by each respondent in each month. α_i represents respondent fixed effects. ε_{it} is the disturbance term. All variables are at the survey respondent level. Consequently, regressions are also conducted at the respondent level.

5.2 Standard errors and probability weighting

We conduct our baseline estimation through two-way fixed-effects regressions with respondent and time fixed-effects. We use so-called "CV1" clustered heteroscedasticity-robust standard errors for inference. This choice is comforted by our relatively large number of observations. MacKinnon et al. (2022) state that when the number of respondents is large and clusters are homogenous, "CV1" and the more conservative "CV3" standard errors yield similar inference. This inference is not excessively liberal.

We apply probability weights to all our regressions for external validity reasons. We thus use weighted least squares. In fixed effects estimations weights cannot vary

[5] Financial activities, professional and business services and public administration loosely map onto "administration" in our dataset.

within units. Therefore, we employ the average sampling weight by respondent in all estimations. If sampling is exogenous, weighting does not improve consistency relative to OLS. Solon et al. (2015) therefore argue that weighted least squares may address external validity issues. However, it does not perform worse (nor does it perform better) than OLS under over or under-sampling. Solon et al. (2015) further suggest that researchers check for model misspecification by running the same regression with and without weights. If both sets of results diverge, this may indicate misspecification. We execute this test and find qualitatively similar results across weighted and unweighted specifications.[6]

5.3 Panel attrition

The panel dataset used in this paper is highly unbalanced. Appendix A2 provides detailed descriptive statistics regarding attrition occurring in our estimation sample. The average number of time periods used per respondent in the estimation sample is 4.8, out of eleven total time periods.

A lot of respondents enter or exit our sample at different moments in time. Two-way fixed effects help to address this issue (Wooldridge, 1995, 2021). However, non-random exit could bias our results if it occurs on a respondent and time varying basis. We therefore run the so-called BGLW test for attrition bias (Becketti et al. (1988). This test investigates whether exit from our sample is informative, conditional on the regressors and fixed-effects employed in the model (see, e.g., Alderman et al., 2001, p.88). The test results reveal that exit from the panel is not significantly related to the dependent variables. The results thus suggest that estimates do not suffer from an attrition bias.

5.4 Instrumental variable approach

Respondents may decide to send apprentices to work from home for time-varying unobserved reasons that might bias our baseline estimates. For instance, Morikawa (2022) suggests that self-selection into working from home occurs, based on expected productivity levels. Emanuel and Harrington (2023) add that individuals may select into working from home based on pre-existing productivity, ambition and motivation. However, we want to isolate the working from home effect on workplace learning.

Therefore, we additionally conduct instrumental variable estimations that follow a "shift-share"-type approach (Breuer, 2022). Concretely, we exploit responses of occupations to changes in working from home regulation. We differentiate between three policy regimes: (1) no regulation regarding working from home, (2) regulation recommending working from home wherever possible, (3) regulation making working from home compulsory whenever possible. As discussed in detail below, we calculate the occupation-specific average of working for home for each of the six time periods during which these three policy regimes were in place. We then calculate the respondent-specific instrument based on the initial share of apprentices in each training occupation. Finally, we calculate the occupation-specific average of working from home in the policy regime period.

Figure 3 shows the proportion of apprentices working from home in our sample each month. The lower portion of the figure shows the duration of the six policy regime periods in days. The proportion of apprentices working from home peaked in March 2021, as working from home was compulsory wherever possible. This proportion then progressively declined until December 2021. After a short surge in early 2022, the proportion of apprentices working from home decreased to circa 4% in March 2022.

We thus instrument the potentially endogenous $WorkingfromHome_{it}$ variable with instrument z_{ip}. p denotes each federal policy regime period, the time of which is measured in days. g_{op} is the occupation-level fraction of apprentices working from home in occupation o during policy regime period p. The share of apprentices in each occupation, s, measures exposure to these occupation-level fractions for each respondent. The instrument z_{ip} is constructed as follows:

$$z_{ip} = \sum_{o=1}^{253} s_{i,o,t_{0,i}} * g_{op}$$

where o denotes occupation: there are 253 occupations in total in our dataset. $t_{0,i}$ denotes the initial period in which we observe respondent i, i.e. the first month in which we observe respondent i in our dataset.

s_{i,o,t_0} measures the share of apprentices in the occupation. It represents the exposure of respondent i to g_{op} in the initial period t_0, defined below. It is the "share" variable. We must assume that $s_{i,o,t_{0,i}}$ is exogenously defined by respondents. Goldsmith-Pinkham et al. (2020) show that the exogeneity of s_{i,o,t_0} is a sufficient condition for the exogeneity of the instrument to hold. If respondents chose this initial share precisely because of working from home and how it is susceptible of impacting workplace learning, this may violate the exogeneity condition. However, it seems implausible that respondents chose to recruit apprentices specifically in certain occupations because of this. It is much more likely that apprentices were recruited in given occupations because that is where their respective firm's main activity lies.

[6] Results can be produced upon request.

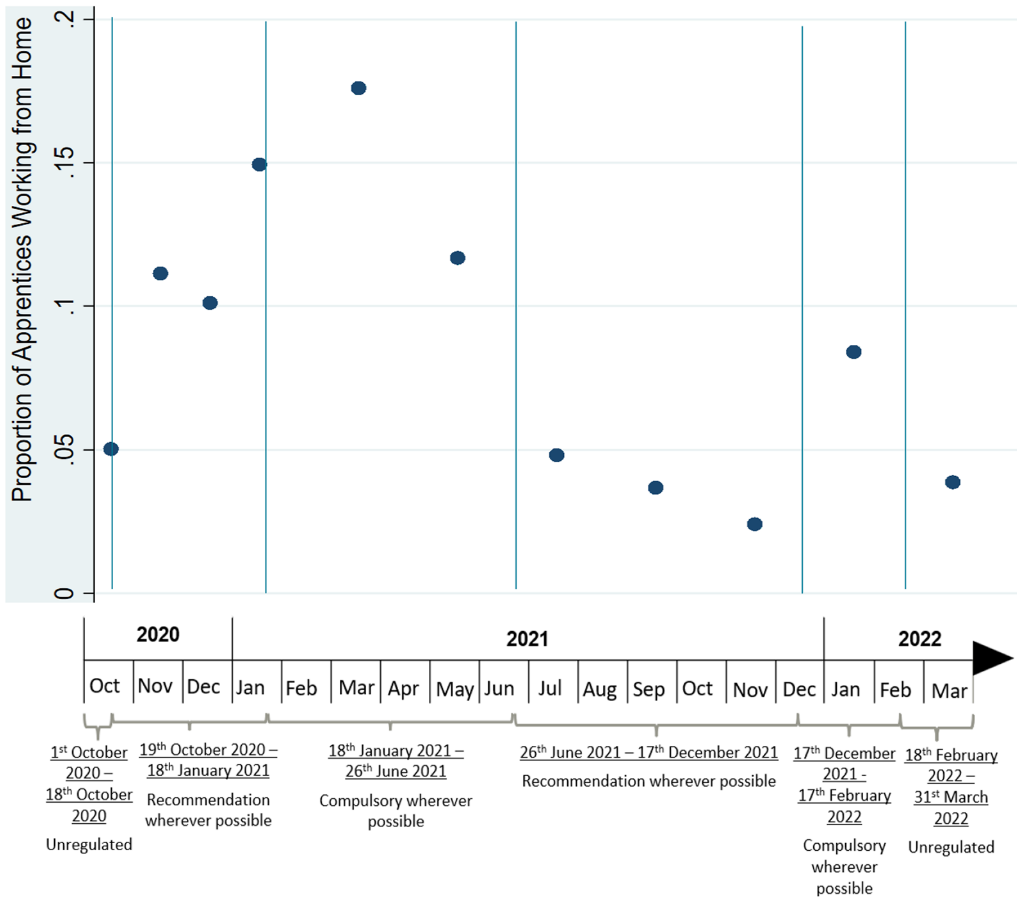

Fig. 3 Working from Home and Policy Regime Changes in Each Month of the Sample. Notes: The figure shows the development of the proportion of apprentices working from home over the time for the months for which we use data. The vertical blue lines represent times of policy regime changes. The duration of the six federal policy regime periods is shown below the months. Source: Authors' Own Elaboration and Federal Council (2020a, 2020b, 2022), Federal Office for Public Health (2022)

$$s_{i,o,t_0} = \frac{Number\ of\ apprentices\ in\ occupation\ o\ in\ initial\ month\ t_0\ reported\ by\ respondent i}{Total\ number\ of\ apprentices\ (in\ initial\ month\ t_0\ and\ respondent\ i)}$$

Lagged shocks to g_{op} may endogenously affect current shares, $s_{i,o,t}$. Following Goldsmith-Pinkham et al. (2020), we thus only use the initial share at time t_0 for each respondent because these shares may vary endogenously across time. Borusyak et al. (2022) show that if an initial share is used, the exogeneity of the instrument can hold.

g_{op} defines the occupation-level fraction of apprentices working from home in occupation o, if the day of the response is within the policy regime period p. It is the "shift" variable. The instrument thus represents a respondent-level weighted sum of exposure to occupation-level "shifts" (Breuer, 2022) in each working from home policy period p.

$$g_{op} = \frac{Number\ of\ apprentices\ working\ from\ home\ in\ occupation\ o\ during\ policy\ regime\ period\ p}{Total\ number\ of\ apprentices\ working\ in\ occupation\ o\ during\ policy\ regime\ period\ p}$$

Notowidigdo (2020) highlights that for exogeneity, the "shift" variable, g_{op} must be uncorrelated with *respondent level* time-varying unobserved factors (ε_{it}). Respondent i has control over whether they send their apprentice(s) to work from home. However, respondent i does not have control over the occupation-level average percentage of apprentices working from home (Breuer, 2022). The instrument thus purges our endogenous variable of variation due to endogenous and time-varying respondent-level factors. Specifically, the instrument cannot be driven by our respondent-level outcome variables, ruling out reverse causality. Breuer (2022, p.8) specifies: "*To reduce the number of possibly confounding factors, [shift-share] instruments focus on plausibly exogenous dimensions of the components making up the treatment.*" Using the occupation-level average percentage of apprentices working from home thus removes the respondent-idiosyncratic component of the working from home decision.[7]

We estimate a weighted instrumental variable estimation model with respondent-level clustered standard errors. We include occupation fixed effects to account for the unobserved heterogeneity of occupations regarding their ability to implement working from home. Occupation fixed effects are necessary, as within-occupation variation across time is the exogenous variation in the instrument we want to leverage. Therefore, our instrument leverages *within occupation* changes to exogenous variations in working from home policy regimes, rather than *between occupation* variation in working from home. In instrumental variable estimation, we continue to cluster our standard errors at the respondent level. This is in line with our resort to the exogeneity of the shares s_{i,o,t_0}. These shares are constructed at the respondent level, and arguably exogenous. Standard errors clustered at the respondent level should therefore adequately capture the asymptotic variance of the shift-share instrument estimator (Borusyak et al., 2022).

Instrumental variable estimation takes place as follows:

First Stage Equation:

$$\begin{aligned} WorkingfromHome_{it} =& \tau_0 + \tau_1 z_{ip} \\ &+ \tau_2 X'_{it} + \gamma_o \\ &+ \delta_t + u_{it} \end{aligned} \tag{3}$$

We retain the fitted values from this first stage regression, $\widehat{WorkingfromHome}_{it}$. γ_o are occupation fixed effects. X'_{it}, δ_t have the same interpretation as described in Sect. 5.1.

The two outcome equations are as follows:

$$\begin{aligned} Practical\ Knowledge_{it} =& \beta_0 + \beta_1 \widehat{WorkingfromHome}_{it} \\ &+ \beta_2 X'_{it} + \gamma_o + \delta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} Theoretical\ Knowledge_{it} =& \varphi_0 + \varphi_1 \widehat{WorkingfromHome}_{it} \\ &+ \varphi_2 X'_{it} \\ &+ \gamma_o + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

6 Results

6.1 Baseline results and heterogeneity analysis

Table 2 presents results stemming from Eqs. (1) and (2). Columns (4) and (8) are our preferred specifications for "Practical Knowledge" and "Theoretical Knowledge", respectively.

Our results provide evidence in favour of hypothesis H1. They are robust to the omission of company-level control variables as well as alternative working activities. The coefficient on the working from home regressor in column (4) of Table 2, our preferred specification. It is negative and statistically significant at 1%. Working from home impedes practical workplace learning relative to frequenting the workplace. The magnitude of the coefficient represents circa 19% of the standard deviation of "Practical Knowledge". A unit change in working from home may thus induce a change in Practical Knowledge representing almost a fifth of the latter variable's standard deviation. Without being excessive, the effect of working from home on Practical Knowledge is of economic interest.

Our results also lend support to hypothesis H2. Working from home has an insignificant effect on theoretical knowledge. This indicates that practical knowledge is less transmissible remotely than theoretical knowledge. The insignificance of the relationship between working from home and theoretical knowledge may occur for multiple reasons. First, the transmission of practical knowledge

[7] Blandhol et al. (2022) highlight that another necessary condition for instrumental variable estimation to be "weakly causal". This condition is "rich covariates". This happens when the linear projection of the instrument on covariates is equal to the conditional expectation function of the instrument as a function of the covariates. We argue this is the case here. Our "shift-share" instrument is exogenously determined on an occupational-level, and thus independent of the covariates, which are determined by respondents at a finer level. In this case, any regression including a constant will have "rich covariates". Out of bounds predictions in the first stage regression may also cause the linear projection of the instrument on covariates to differ from the conditional expectation function of the instrument as a function of the covariates. This may be of concern here as our endogenous variable is comprised between 0 and 1. When we run a separate instrumental variable regression excluding out-of-bounds first-stage predicted values, we obtain qualitatively aligned results. The coefficient magnitudes are virtually identical to instrumental variable results shown in this paper. This reflects the lower number of observations, leading to less statistical power. Results can be produced upon request.

Table 2 Baseline regression results

Dependent variable	Practical knowledge				Theoretical knowledge			
Estimation	**(1) POLS**	**(2) FE without Other Working Activities**	**(3) FE no company Controls**	**(4) FE with company Controls**	**(5) POLS**	**(6) FE without other Working Activities**	**(7) FE no company Controls**	**(8) FE with company Controls**
Working from home	−0.184***	−0.0835***	−0.0931***	−0.0867***	−0.0458	0.0326	0.0179	0.0251
	(0.0380)	(0.0313)	(0.0318)	(0.0317)	(0.0338)	(0.0296)	(0.0293)	(0.0292)
Observations	11,450	11,450	11,450	11,450	11,411	11,411	11,411	11,411
Within R-squared	0.069	0.036	0.033	0.037	0.036	0.032	0.031	0.034
Number of respondents	3,140	3,140	3,140	3,140	3,131	3,131	3,131	3,131
Respondent FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent controls	Yes	Yes	No	Yes	Yes	Yes	No	Yes

The table shows weighted least squares (WLS) coefficients and robust standard errors clustered at the respondent level in parentheses. POLS = Pooled OLS. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical knowledge and theoretical knowledge of apprentices, respectively. They have a 5-Point Likert scale from substantially worse (−2) to substantially improved (2). Working from Home indicates whether the company has apprentices who are working from home. Company controls are listed in Table 1. The POLS columns show the overall R-squared rather than the within R-squared

may require relatively more social interactions, such as guidance, observation, feedback (Billett, 2001; Gibbs et al., 2023; Yang et al., 2022). Not frequenting the workplace may deprive apprentices comparatively more of the acquisition of practical knowledge. This may also decrease motivation and commitment to the job (Eraut, 2007). Second, transmission of theoretical knowledge may occur through channels other than mimetic learning. Mimetic learning is relatively more important for the transmission of practical knowledge and more difficult to apply in remote settings (Billett, 2014). Third, in-person practical activities, such as operating heavy machinery, cannot be pursued remotely (ILO, 2021). Instead, apprentices work from home might potentially be given a larger fraction of non-productive tasks to perform, e.g. the study of abstract notions. These tasks may bear more relevance to the theoretical knowledge of apprentices.

Table 10 of the appendix tests whether the effect of working from home is statistically significantly different across various federal working from home policy regime periods. For both theoretical and practical knowledge, we find that working from home does not have a significantly lower or higher effect during unregulated working from home periods. Similarly, we find that working from home does not have a significantly lower or higher effect during periods in which working from home was *not* compulsory wherever possible (i.e. periods in which working from home was either unregulated or recommended). We however acknowledge that the true effect of working from home on workplace learning may be heterogeneous across these periods. We may simply lack statistical power to detect it.

6.2 Heterogeneity analysis

Table 3 tests hypotheses H3 and H4. Columns (1) and (2) test hypothesis H3. They include an interaction term between the work from home (WFH) regressor and a medium and large companies dichotomous indicator variable. Columns (3) and (4) evaluate hypothesis H4. They contain an interaction term between the work from home regressor and a dichotomous variable indicating whether apprentices work in an occupation in which working from home is relatively more prevalent.

Hypothesis H3 suggests that working from home impedes workplace learning in large companies relatively less. Table 3 does not support hypothesis H3. In columns (1) and (2), the interaction term between medium and large company and working from home is statistically insignificant. Apprentices working from home in medium and large companies do not experience a significantly weaker impact of working from home on practical and theoretical knowledge than apprentices pursuing their apprenticeship in small companies.

Consequently, it is unlikely that large discrepancies in digital investments between small and medium and large companies have led to disproportionately adverse learning outcomes for those apprentices working from home in smaller companies. It is possible that smaller companies attenuate the adverse effect of sub-par digital infrastructure on workplace learning. To this end, they may use increased support, e.g. help in daily tasks, more attention given to feedback, complaints, more human contact (Hammann et al., 2008).

Hypothesis H4 suggests that working from home impedes workplace learning relatively more in occupations in which

Table 3 Heterogeneity of working from home's effect by company size and occupation

Heterogeneity	**(1) Company size**	**(2) Company size**	**(3) Working from home prevalence**	**(4) Working from home prevalence**
Dependent Variable	**Practical knowledge**	**Theoretical knowledge**	**Practical knowledge**	**Theoretical knowledge**
WFH	−0.0908**	0.0210	−0.135***	−0.0239
	(0.0440)	(0.0391)	(0.0395)	(0.0351)
Medium and Large company # WFH	0.00899	0.00875		
	(0.0604)	(0.0570)		
WFH Prevalent Occupation			−0.0837	0.0128
			(0.130)	(0.139)
WFH Prevalent Occupation # WFH			0.0604	0.0614
			(0.0533)	(0.0481)
Observations	11,450	11,411	11,450	11,411
Within R-squared	0.037	0.034	0.037	0.034
Number of respondents	3,140	3,131	3,140	3,131

WFH signifies "working from home". The table shows WLS coefficients and robust standard errors clustered at the respondent level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All columns include month and respondent fixed effects. The dependent variable in columns (1) and (3) is Practical knowledge, in columns (2) and (4) is Theoretical knowledge. Columns (1), (2) include an interaction term between a medium and large company indicator variable and the work from home indicator variable, whilst columns (3), (4) comprise an interaction term between the work from home prevalence in occupation indicator variable, and the work from home indicator variable. Medium and large companies are defined as companies with 50 or more employees, whilst work from home prevalent occupations are IT and administration

working from home is less prevalent. Table 3 does not lend support to hypothesis H4, either. Columns (3) and (4) demonstrate that the interaction term between the working from home regressor and the working from home prevalence of occupation indicator variable is insignificant. Apprentices pursuing an apprenticeship within an occupation in which working from home is more prevalent do not experience a significantly stronger impact of working from home on theoretical knowledge or practical. Hence, we do not find conclusive support for hypothesis H4.[8]

This is in contradiction with Etheridge et al. (2020), Bartik et al. (2020) and Morikawa (2022). Therefore, it is probable that occupations in which few tasks are suitable for working from home also have low prevalence of working from home. The latter interpretation would corroborate the findings of Bailey and Kurland (2002). Bailey and Kurland (2002) assert that workers are more likely to be willing to work from home, and their managers willing to let them work from home, in occupations in which a large proportion of tasks to be accomplished can be performed remotely. This would entail a self-selection into working from home of workers in occupations with high working from home prevalence.

6.3 Instrumental variable estimation results

Table 4 shows the results from the instrumental variable estimation. Specifications become increasingly demanding as we move towards the right. Our preferred specifications are depicted in columns (4) and (8). Results are highly robust to changes in controls and/or fixed effects vectors.

In the first stage equation, the instrument has a significant positive effect on working from home, the endogenous variable. We report the Sanderson-Windmeijer (2016) first stage F-Statistics on the excluded instrument. This statistic corresponds to the Kleibergen-Paap (2006) "rk Wald statistic" in exact identified instrumental variable estimations.[9] These F-Statistics are large, suggesting strong instrument relevance.

The instrumental variable results support the baseline results for hypotheses H1 and H2. Working from home has a large and significantly negative effect on Practical Knowledge in all specifications. Working from home does not significantly impact Theoretical Knowledge. These results corroborate baseline two-way fixed effects results. They lead us to the same conclusions.

[8] We replicate Table 3 with instrumental variable estimation, using the instrumental variable constructed in subsection 5.4. The interaction term was itself instrumented using an interaction between the instrument and the relevant dummy variable (medium and large company, and working from home prevalent occupation, respectively). Results can be produced upon request. They are qualitatively similar to baseline two-way fixed-effects model results.

[9] Due to the highly probable presence of heteroscedasticity, autocorrelation and clustering in the error terms, we do not report the Stock-Yogo (2002) critical values. This is in line with recommendations from Baum et al. (2007) and Bazzi and Clemens (2013). Again, following Baum et al. (2007), we compare the F-Statistic we obtain to the value of 10 as a rule of thumb. If the value of the instrument exceeds 10, weak identification should not represent too much of a problem.

Table 4 Instrumental variable results

Dependent variable	Practical knowledge				Theoretical knowledge			
Estimation	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Working from home	− 0.506***	− 0.335***	− 0.322***	− 0.337***	0.123	0.0681	0.0576	0.0675
	(0.0797)	(0.108)	(0.108)	(0.110)	(0.0825)	(0.113)	(0.113)	(0.115)
Observations	11,450	11,450	11,450	11,450	11,411	11,411	11,411	11,411
Month fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Occupation fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other working activities	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Respondent controls	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Sanderson-Windmeijer (2016) F-Statistic for underidentification and Weak Identification	250.01	137.19	134.49	133.36	248.01	138.22	135.67	134.42
First Stage coefficient of instrument	0.492*** (0.031)	0.534*** (0.046)	0.531*** (0.046)	0.524*** (0.045)	0.491*** (0.031)	0.540*** (0.046)	0.536*** (0.046)	0.529*** (0.046)

The table shows weighted two-stage least squares coefficients. The coefficient shown for "Working from Home" is the second stage coefficient of an instrumental variable estimation. Robust standard errors clustered at the respondent level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical knowledge and theoretical knowledge of apprentices, respectively. They have a 5-Point Likert scale from substantially worse (− 2) to substantially improved (2). Details of each variable are elicited in Sect. 4.3

Considering columns (4) and (8) of Table 4, the magnitude of the second stage coefficients of Working from Home is 0.279 and 0.0377, respectively. This represents 59.74% and 7.42% of the standard deviation of Practical Knowledge and Theoretical Knowledge, respectively. Regarding the Practical Knowledge specification, our preferred instrumental variable estimates indicate that a unit change in the fitted values of Working from Home lead to a decrease of over half of Practical Knowledge's total variability. This effect is of large magnitude, making it economically significant, in addition to being statistically significant. In the baseline two-way fixed effects specification (column (4) of Table 2), we found that the magnitude of the coefficient on Working from Home represents only almost a fifth of the standard deviation of "Practical Knowledge". The magnitude of instrumental variable estimates is thus relatively larger than the magnitude of the baseline two-way fixed effects estimates. This difference could occur for two reasons:

First, this difference in magnitude may be due to endogenous sorting into working from home. Respondents may only let those apprentices work from home whose learning would be unharmed by this new mode of working. This would cause downwards bias in OLS two-way fixed effects estimates (see Xu & Jaggars, 2013, for a similar interpretation of instrumental variable versus OLS coefficient magnitude). For this reason, we trust the internal validity of instrumental variable estimation more than the internal validity of baseline OLS two-way fixed effects estimation.

Second, the difference in magnitude between OLS two-way fixed effects estimates and instrumental variable estimates may indicate that voluntary working from home genuinely harms workplace learning relatively less than working from home under federal mandates. However, the internal validity of our OLS two-way fixed effects estimates is questionable, precisely due to endogenous sorting. Consequently, we cannot assert with certainty that voluntary working from home harms workplace learning less than federally mandated working from home.

Our instrumental variable results suffer from one notable limitation. Generalisation of instrumental variable results need to be treated with caution. We cannot necessarily extrapolate our instrumental variable results to a firm that, in the future, wishes to allow apprentices to work from home on a voluntary basis. This is because the effects our instrumental variable estimations are related to federal policies regarding working from home. They do not identify the effect of working from home on workplace learning when firms voluntarily choose to allow apprentices to work from home.

6.4 Robustness checks

This subsection discusses three robustness checks. The first tests multiple hypothesis testing adjustment. The second focuses on the subsample of apprentice-trainers to investigate the potential presence of measurement error in baseline results. The third robustness check accounts for time elapsed between responses.

The first robustness check addresses the issue that we execute multiple regressions to investigate the effect of working from home on Practical and Theoretical Knowledge. Our chosen α, threshold for significance and type 1 error probability, is 5%. Due to the multiplicity of tests, and because these tests are not fully dependent, the probability of type 1 error surges over 5%. We reject the null hypothesis of no effect of working from home on Practical Knowledge five times in this paper. However, we run in total ten regressions to investigate the effect of working from home on Practical and Theoretical Knowledge. We therefore apply strong family-wise error rate (FWER) control to keep α under 5% by using the Romano and Wolf (2016) methodology. Table 7 shows unadjusted probability values (p-values) obtained directly in the estimations. It also contains the corresponding Romano and Wolf (2016) adjusted p-values. In all cases, adjusted inference remains identical to unadjusted inference (so do Holm-adjusted probability values).

The second robustness test hypothesises that apprentice-trainers can evaluate the evolution of apprentices' workplace learning most accurately. They have the highest proximity to apprentices relative to all other respondents in our sample. Therefore, their evaluations regarding apprentices' learning bear the highest level of accuracy and the lowest level of measurement error. Appendix Table 5 shows that our results are qualitatively robust to the subsample of observations including only apprentice-trainers. The coefficient for "Practical knowledge" remains negative and significant. The coefficient also remains insignificant for "Theoretical knowledge".

Finally, the third robustness test addresses the unbalanced characteristic of our panel. Respondents were followed over different durations. However, our baseline estimates do not account for the elapsed time between observations of a respondent. Therefore, two robustness tests restrict the sample to observations that are at most either two or fourth month apart for each respondent. Tables 8 and 9 in the Appendix display the results. The results are qualitatively similar to the baseline results. Table 8 shows quasi-identical magnitudes of the coefficients. The coefficient in the "Practical Knowledge" specification is relatively larger in Table 9, but the inference is also qualitatively similar.

7 Conclusion, study limitations and policy recommendations

Working from home is here to stay. The reorganisation of working modes it incurs has ramifications for human resources development strategies. This paper adds to the current strand of literature on the effects of the COVID19-induced generalisation of working from home on workplace learning. Our original contribution has wider ramifications for the labour productivity of the Swiss labour force. It is the first study taking steps towards the causal evaluation of working from home's impact on the acquisition of both practical and theoretical knowledge in the workplace.

We find that working from home significantly impedes the acquisition of practical knowledge relative to frequenting the workplace. However, it does not statistically significantly impede the acquisition of theoretical knowledge relative to frequenting the workplace. We find insufficient empirical evidence to support the hypothesis that the effect of working from home on workplace learning is heterogenous across company size. Furthermore, we find no evidence that working from home impedes workplace learning more in occupations in which working from home is less prevalent.

We use two identification strategies to test whether working from home affects practical and theoretical knowledge. We use OLS with two-way fixed-effects and an instrumental variable approach, using a "shift-share"-type instrument. The instrumental variable approach was implemented to surmount issues of endogeneity arising from time-variant unobserved heterogeneity. Respondents, in certain circumstances, could decide whether to send apprentices working from home for endogenous reasons. Endogenous self-selection into working from home could have occurred (Emanuel & Harrington, 2023; Morikawa, 2022). This can induce downwards bias in OLS estimation as apprentices who work from home may be those for whom working from home would be the least detrimental.

Both estimation methods, OLS and instrumental variable, yield qualitatively similar results. Instrumental variable results are larger in magnitude than corresponding OLS two-way fixed-effects estimates. This is in line with the findings of Xu and Jaggars (2013) as they compare OLS to instrumental variable results. Our results are also robust to a wide range of robustness checks. For instance, within each respondent, we sequentially restrict the time periods used in two-way fixed-effects estimations to at most two and then four months apart. Furthermore, we only consider responses from apprentice-trainers, who have the closest professional proximity to apprentices. They are in the best position to judge apprentices' learning. These robustness checks yield results that are qualitatively aligned with baseline results.

However, our study suffers from four main limitations. First, though we employ two alternative identification strategies, some concerns regarding endogeneity remain. Second, our survey data could contain measurement error in the subjective measures of "Practical Knowledge" and "Theoretical Knowledge". Third, our results for Swiss apprentices might not hold for other countries or age groups. Finally, our data do not allow us to individually test the specific channels through which working from home affects workplace learning.

Our findings nonetheless allow us to draw policy implications. From a policy perspective, mandating working from home on a federal level, even only "wherever possible", is detrimental to apprentices' practical knowledge. When firms can choose to allow certain apprentices to work from home or not, the negative effect of working from home on practical knowledge is attenuated. When apprentices are working from home, their respective firm's focus should be placed on mitigating the detrimental impact working from home may have on practical knowledge. To this end, this paper's recommendations are to ensure the widespread availability of high-quality digital infrastructure. Moreover, frequent contact between apprentices and other employees must be maintained remotely. Both of these recommendations serve to safeguard apprentices' professional motivation and maintain their level of engagement with the content at hand. In turn, heightened motivation should contribute to the preservation of practical (and theoretical) knowledge.

Future studies may rely on more objective measures of apprentices' learning progress such as final test scores. Future research should also evaluate the external validity of our results and may rely on randomised controlled trials to reinforce internal validity. Particularly the heterogeneity of the effect for mandatory and non-mandatory working from home should be explored in more detail. An interesting avenue for future research would be the investigation of spillover effects of working from home. How is the learning of one apprentice affected if other apprentices in the same firm, or other employees, are working from home? Is this effect exacerbated if the apprentice his or herself works from home as well?

See Tables 5, 6, 7, 8, 9, 10.

Appendix

See Tables 5, 6, 7, 8, 9, 10.

Table 5 Baseline regression results—subsample of apprentice trainers

Dependent variable	Practical knowledge				Theoretical knowledge			
Estimation	**(1) POLS**	**(2) FE without other Working Activities**	**(3) FE no company Controls**	**(4) FE with company Controls**	**(5) POLS**	**(6) FE without other Working Activities**	**(7) FE no company Controls**	**(8) FE with company Controls**
Working from home	−0.156**	−0.0943*	−0.102**	−0.0995**	−0.0255	0.0204	0.00998	0.0117
	(0.0625)	(0.0500)	(0.0506)	(0.0505)	(0.0530)	(0.0429)	(0.0439)	(0.0428)
Observations	3,831	3,831	3,831	3,831	3,817	3,817	3,817	3,817
Within R-squared	0.076	0.043	0.042	0.044	0.048	0.047	0.048	0.050
Number of respondents	1,028	1,028	1,028	1,028	1,027	1,027	1,027	1,027
Respondent FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent controls	Yes	Yes	No	Yes	Yes	Yes	No	Yes

The table shows WLS coefficients and robust standard errors clustered at the respondent level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical knowledge and theoretical knowledge of apprentices, respectively. They have a 5-Point Likert scale from substantially worse (− 2) to substantially improved (2). Working from Home indicates whether the company has apprentices who are working from home. Company controls comprise the variables Prevalence *Short-Time Work*, Sanitary Protocol, Financial Distress, Risk Bankruptcy and Temporary Closure. Other Activities include company-attributed homework and no company-provided training. Details of each variable are elicited in Sect. 4.3. The POLS columns show the overall R-squared rather than the within R-squared

Table 6 Descriptive statistics regarding attrition

Variable	Mean	Minimum	Maximum	Observations	Number of respondents
Number of time periods used in estimation sample by respondent	3.646	2	11	11,450	3,140

Descriptive statistics are presented for the estimation sample in the "Practical knowledge" specification

Table 7 Multiple hypothesis testing adjustment

Statistically significant estimate of "working from home" in "practical knowledge" specifications	Unadjusted probability value (p-value)	Romano and Wolf (2016) adjusted probability value	Holm adjusted probability values
Column (4) Table 2	0.0062	0.0030	0.0180
Column (4) Table 4	0.0021	0.0020	0.0100
Column (4) Table 5	0.0491	0.0410	0.0480
Column (4) Table 8	0.0250	0.0190	0.0350
Column (4) Table 9	0.0147	0.0090	0.0080

We have run ten regressions in order to investigate the effect of working from home on Practical Knowledge and on Theoretical Knowledge. In five of these specifications (listed in the table), we find a significant effect. The second column of this table shows unadjusted p-values obtained through estimations. The overall type 1 error probability exceeds 5% in this column. Therefore, the third column applies strong FWER control to keep the type 1 error probability under or equal to 5%. The third column shows p-values that have been adjusted, with strong FWER control applied (Romano & Wolf, 2016). The fourth column shows Holm-adjusted p-values

Table 8 Subsample analysis—observations that are at most four months apart for each respondent

Dependent variable	Practical knowledge				Theoretical knowledge			
Estimation	(1) Pooled OLS	(2) FE without Other Working Activities	(3) FE no company Controls	(4) FE with company Controls	(5) POLS	(6) FE without other Working Activities	(7) FE no company Controls	(8) FE with company Controls
Working from home	−0.177***	−0.0781**	−0.0871**	−0.0810**	−0.0513	0.0298	0.0166	0.0216
	(0.0406)	(0.0357)	(0.0362)	(0.0361)	(0.0359)	(0.0338)	(0.0335)	(0.0333)
Observations	9,101	9,101	9,101	9,101	9,069	9,069	9,069	9,069
Within R-squared	0.070	0.034	0.032	0.035	0.038	0.031	0.031	0.033
Number of respondents	2,534	2,534	2,534	2,534	2,522	2,522	2,522	2,522
Respondent FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other working activities	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Respondent controls	Yes	Yes	No	Yes	Yes	Yes	No	Yes

The table shows weighted least squares (WLS) coefficients and robust standard errors clustered by respondent in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical and theoretical knowledge of apprentices. They have a 5-Point Likert scale from worse (−2) to improved (2). Working from Home indicates whether the respondent has apprentices working from home. Company controls comprise the variables Prevalence *Short-Time Work*, Sanitary Protocol, Financial Distress, Risk Bankruptcy and Temporary Closure. Other Activities include homework and no company-provided training

Table 9 Subsample analysis –observations that are at most two months apart for each respondent

Dependent variable	Practical knowledge				Theoretical knowledge			
Estimation	**(1) POLS**	**(2) FE without Other Working Activities**	**(3) FE no company Controls**	**(4) FE with company Controls**	**(5) POLS**	**(6) FE without other Working Activities**	**(7) FE no company Controls**	**(8) FE with company Controls**
Working from home	−0.198***	−0.1000**	−0.110**	−0.105**	−0.0784**	0.0139	0.000508	0.00645
	(0.0456)	(0.0425)	(0.0429)	(0.0430)	(0.0399)	(0.0392)	(0.0392)	(0.0388)
Observations	7,142	7,142	7,142	7,142	7,112	7,112	7,112	7,112
Within R-squared	0.075	0.040	0.038	0.041	0.043	0.031	0.029	0.032
Number of respondents	2,178	2,178	2,178	2,178	2,169	2,169	2,169	2,169
Respondent FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other working Activities	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Respondent controls	Yes	Yes	No	Yes	Yes	Yes	No	Yes

The table shows weighted least squares (WLS) coefficients and robust standard errors clustered at the respondent level in parentheses. POLS = Pooled OLS. *** p < 0.01, ** p < 0.05, * p < 0.1. Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical knowledge and theoretical knowledge of apprentices, respectively. They have a 5-Point Likert scale from substantially worse (− 2) to substantially improved (2). Working from Home indicates whether the company has apprentices who are working from home. company controls comprise the variables Prevalence *Short-Time Work,* Sanitary Protocol, Financial Distress, Risk Bankruptcy and Temporary Closure

Table 10 Effects of working from home on workplace learning according to federal working from home regulation periods

Dependent variable	Practical knowledge	Practical knowledge	Theoretical knowledge	Theoretical knowledge
Working from home	−0.0928***	−0.0929***	0.00199	0.00204
	(0.0353)	(0.0353)	(0.0335)	(0.0335)
Working from home * not compulsory working from home period		0.0142		0.0533
		(0.0364)		(0.0398)
Working from home * unregulated working from home period	0.0469		0.0277	
	(0.0715)		(0.0692)	
Working from home * recommended working from home period	0.00824		0.0580	
	(0.0385)		(0.0402)	
Observations	11,450	11,450	11,411	11,411
Month fixed effects	Yes	Yes	Yes	Yes
Respondent fixed effects	Yes	Yes	Yes	Yes
Other working activities	Yes	Yes	Yes	Yes
Respondent controls	Yes	Yes	Yes	Yes

The table shows weighted least squares (WLS) coefficients and robust standard errors clustered at the respondent level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Practical knowledge and Theoretical knowledge capture the impact of COVID19 on practical knowledge and theoretical knowledge of apprentices, respectively. They have a 5-Point Likert scale from substantially worse (− 2) to substantially improved (2). Working from Home indicates whether the company has apprentices who are working from home. Company controls comprise the variables Prevalence Short-Time Work, Sanitary Protocol, Financial Distress, Risk Bankruptcy and Temporary Closure. The "Not Compulsory Working from Home Period" is composed of periods during which working from home was either unregulated or recommended by the Swiss Federal Council

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Author contributions
Both authors contributed to the paper. GM's contributions included the empirical analysis (Sects. 4, 5 and 6), mainly comprising the execution of all regressions, robustness checks and interpretation of results. GM also played

an important role in the elaboration of the literature review by aggregating literature sources, interpreting extant findings and utilising them within the framework of the current paper. GM thereby additionally took part in the construction of hypotheses to be tested, the introduction and conclusion (containing policy recommendations). TB provided instrumental feedback and revisions regarding all sections of the paper and devised the theoretical framework containing the causal mechanisms that are tested in the empirical analysis. TB also supplied essential guidance regarding the construction of the equations leading to our results. The survey data employed in this paper required cleaning and pre-processing in order to become analysable, which was done by TB, without whom data generated through our surveys would have been unusable.

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Availability of data and materials
The datasets analysed in the current study are not publicly available due strict confidentiality and data privacy regulations but are available from the corresponding author on reasonable request.

Declarations

Competing interests
Authors have no competing or conflicting interests to declare.

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