Journal for Labour Market Research

ORIGINAL ARTICLE

Open Access

Continuing vocational training in times of economic uncertainty: an event-study analysis in real time

Christine Dauth[1,2*] and Julia Lang[2]

Abstract

Continuing vocational training (CVT) is a key channel for employees to adapt their skills to changing requirements in the labor market due to structural changes and digitization. The COVID-19 pandemic and the energy crisis as a consequence of the war in Ukraine may have accelerated these developments. Yet, it is unclear how the economic impact of these crises affects individuals' occupational preferences. In this study, we want to investigate how interest in CVT changes in times of economic uncertainty. We use Google Trends data for Germany and apply an event study analysis to examine how interest in CVT developed with the onset of the COVID-19 pandemic and the Russian attack on Ukraine. We find that the interest in CVT strongly declined during the first wave of the pandemic regardless of how severely a region was affected. During the second lockdown, the decline in CVT interest was more pronounced in the eastern German states where we find a general decline in search intensity since March 2020. We also consider different channels that may have influenced the demand for CVT during the pandemic. Overall, we show that during the first 2.5 years of the pandemic, the search intensity for CVT decreased on average by 12 to 19 percent, while the search intensity for online CVT increased by 39 to 45 percent. We also see a decrease in the search intensity for CVT at the beginning of the energy crisis.

Keywords Continuing vocational training, Online training, COVID-19 pandemic, Energy crisis

JEL Classification I18, J24

1 Introduction

The COVID-19 pandemic brought economic uncertainty to many people around the globe. Especially in the early infection waves, governments responded with differing temporary restrictions to social and economic activities to limit the spread of the coronavirus. These restrictions comprised several non-pharmaceutical interventions such as stay-at-home orders, the lockdown of large parts of the economy, the closure of schools and daycare facilities, and stricter hygienic requirements to operate businesses. Because of these measures, unemployment rates and short-time work programs spiked in many countries (OECD 2021), leaving a large part of the population uncertain about their future (Altig et al. 2020; Botha et al. 2021).

This economic shock occurred during ongoing structural changes triggered by the increasing use of IT technologies, robotics, automation, ecological transformations, and the ageing of societies (Autor 2015; Dauth et al. 2021; Genz et al. 2019; Goos et al. 2014). Literature altogether agrees that these developments will change how we work and consequently the skills that companies will demand (Lerch 2022). Indeed, several studies suggest that training has the potential to help workers affected by these changes to adapt. Publicly funded training has been

*Correspondence:
Christine Dauth
christine.dauth@hs-ansbach.de
[1] Ansbach University of Applied Sciences, Ansbach, Germany
[2] Institute for Employment Research (IAB), Nuremberg, Germany

shown to increase job-finding rates for unemployed workers in occupations at high risk of automation (Schmidpeter and Winter-Ebmer, 2021). Moreover, continuing vocational training (CVT) crucially enables workers to transition to tasks or occupations that are less automatable than the previous one (Nedelkoska and Quintini 2018; Tamm 2018). In line with this finding, Janssen et al. (2018) show that firms investing in digital technologies simultaneously increase their training activities. In contrast to these findings, more recent literature suggests that employers adopting advanced digital technologies and workers in occupations that are exposed to substitution or automation are less likely to engage in training than others, partly due to reduced financial support from firms (Brunello et al. 2023, Hess et al. 2023). While training investment seems to be going down, this could be because firms are switching to cheaper online training methods. This highlights the importance of vocational training (CVT) for industries facing major changes.

It is unclear whether the pandemic accelerated the described transformation and how the interest of both workers and employers in CVT in general and in online CVT in particular, aimed at helping workers adapt to these structural changes, will be affected in the future. This paper investigates the impact of governmental responses to the spread of COVID-19 infections on workers' interest in training and how this changed over the onset of the pandemic and beyond. Moreover, we focus on the role of online training in times when face-to-face courses were hampered by social distancing restrictions and hygiene requirements. We also want to investigate whether the interest in CVT was not only specifically influenced by the pandemic but is generally influenced when individuals find themselves in economically uncertain situations. Therefore, we also look at the impact of the energy crisis triggered by Russia's war of aggression on Ukraine.

Evaluating the dynamics of training activities is a delicate matter, as data on CVT are usually only available from annual surveys. Therefore, we exploit Google Trends data on searches for training-related keywords. The underlying idea is that these keywords reflect workers' interest in CVT, which is a necessary precondition for actual CVT participation. As these data are available for periods before and during different stages of the pandemic, we can document how the interest in CVT changed due to the pandemic.

So far, there has been little empirical evidence on the impact of the COVID-19 pandemic on CVT participation. The existing studies have significant drawbacks. Some studies are based on data collected only after the onset of the pandemic (Bellmann et al. 2020; Flake et al. 2021). This implies that the authors cannot compare participation rates in CVT before and after the pandemic outbreak. Other studies, which use data from repeated surveys, can only rely on annual CVT participation rates (BMBF 2022; Jost and Leber 2021). Due to the low frequency of data collection, these studies cannot illustrate how CVT participation evolved during different stages of the pandemic.

Compared to the literature available so far, we provide novel evidence using high-frequency real-time data that has been available since 2004. We find that the interest in CVT strongly decreased at the beginning of the pandemic during the first lockdown. Distinguishing between different German regions (federal states), we show that this decline similarly applied to all regions in the first lockdown, whereas we find substantial differences during the second lockdown and afterwards. In contrast to the overall interest in CVT, the interest in online training courses increased sharply, especially during the lockdown periods. We also find a decline in training interest during the energy crisis in 2022. Finally, we show that different channels might be associated with the interest in CVT. We find that an increase in the interest in videoconferencing tools, emergency daycare, and short-time work is correlated with a decrease in the overall interest in continuing vocational training during the pandemic.

The remainder of the paper is organized as follows: Sect. 2 gives an overview of the development of the pandemic and the accompanying restrictions that potentially affected the supply and demand for CVT. Section 3 summarizes the related literature, Sect. 4 describes the underlying data, and Sect. 5 our empirical strategy. Section 6 presents the results and Sect. 7 concludes.

2 Governmental reactions to the spread of the Coronavirus and potential effects on the supply of and demand for CVT

Germany has been hit by several waves with high numbers of Coronavirus infections. In this study, we focus on the first three waves until May 2021 (see Fig. 1), because the strict measures to contain the virus did not apply thereafter, and continue the analysis until October 2022. In the first as well as in the second and third waves, there were large differences in infections and incidence rates between the 16 federal states.[1] As a result, regional state governments responded with varying degrees of stringency by implementing different restrictions. However, especially at the beginning of the pandemic, all restrictions were relatively severe across all federal states.

The measures taken by the federal and state governments in response to the pandemic can affect both the

[1] Infections describe the absolute number of daily newly registered COVID-19 cases, while incidence rates are usually calculated as the sum of all infections within seven days divided by the population size.

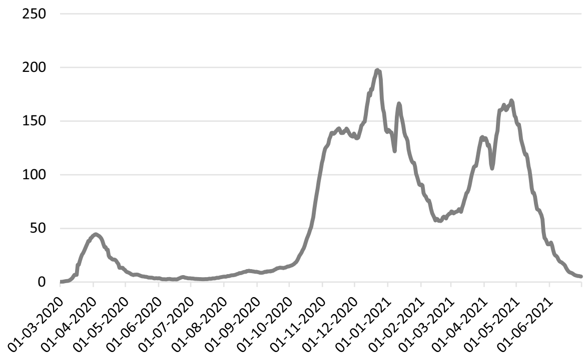

Fig. 1 7-day incidence rates of COVID-19 infections (calculated as the sum of all infections within seven days divided by the population size) in Germany during the pandemic. Source: Corona Datenplattform (RKI 2023)

supply of and the demand for CVT. In our context, CVT refers to planned, organized, and targeted training activities aimed at the acquisition of new skills or the improvement of existing skills by workers. It includes formal (virtual or non-virtual) classroom courses as well as other non-formal or informal forms of training such as on-the-job training, conferences, e-learning, and learning via the Internet or apps (Eurostat 2022). Until the beginning of the pandemic, training courses primarily took place with participants physically present, and online courses played a minor role (Christ et al. 2020). As the pandemic intensified, several measures were implemented in mid-March 2020 to limit the spread of the virus among individuals. With the start of this first lockdown in Germany on March 22, schools and kindergartens were closed and curfews and contact restrictions were imposed in many regions. Classroom training was no longer allowed, and CVT courses had to be interrupted, cancelled, or continued as online courses. These sudden restrictions dramatically limited the possibilities for many training providers to supply in-class training courses (Bellmann et al. 2020).

Soon after the cooldown of the first wave and first deregulations in April 2020, the government again allowed classroom training under certain conditions (e.g., compliance with hygiene regulations, maximum number of participants) in May 2020 (Kohl and Denzl 2020). As the pandemic further progressed, governmental regulations were commonly arranged on the regional rather than on the federal level. Consequently, the conditions training providers had to meet to supply classroom training during the summer and fall of 2020 differed from state to state. Starting mid-December 2020, with the beginning of the second lockdown in Germany (during waves two and three), classroom courses were again prohibited in most federal states which lasted until the spring of 2021. On March 3, 2021, the federal and state governments agreed to gradual regional relaxations depending on a stable incidence rate of fewer than 50 infections per day in a county. Starting on May 19, 2021, face-to-face events were again permitted in all federal states, subject to certain conditions (that could depend on the local regulations).[2]

The overall impact from the supply side is ambiguous: as a result of the difficult conditions to offer training in class, we expect a decline in participation and interest in overall CVT, i.e., non-virtual and virtual training, especially during the lockdowns with strict social-distancing regulations. However, as many training providers expanded their range of online courses in response to the

Table 1 Lockdown periods by date with exemplary restrictions

Phase	Date	Exemplary non-pharmaceutical restrictions and political development
Lockdown 1	March 22, 2020–May 5, 2020	School closures, prohibition to shop/ go to the hairdresser/ leave one's home/ meet more than one friend/ demonstrate Face-to-face classroom training prohibited
Between lockdowns	May 6, 2020–November 1, 2020	No strict non-pharmaceutical measures Classroom training allowed subject to hygiene standards and maximum number of participants
Lockdown 2	November 2, 2020–December 20, 2020 December 21, 2020–May18, 2021	Lockdown "light": less drastic measures than in lockdown 1, e.g., closure of restaurants Lockdown "hard": school closures, prohibition to shop/ go to the hairdresser/ leave one's home/meet more than one friend/ demonstrate Face-to-face classroom training prohibited
After lockdown 2	May 19, 2021- February 23, 2022 February 24, 2022–September 30, 2022	Gradual relaxations of measures on local levels War of Russia on Ukraine

[2] For an overview on different stages of the pandemic see also Table 1.

more difficult conditions for in-classroom courses (Kleinert et al. 2021), we expect interest in online courses in particular to increase.

Beyond the impact on the supply side, the pandemic also influenced the demand side in various ways. First, the working conditions for many employees underwent significant changes due to the measures implemented to control the pandemic. The increased prevalence of remote work and travel restrictions accelerated digitization in numerous areas, necessitating employees to familiarize themselves with new videoconferencing tools for co-working with colleagues and communicating with clients (Kleinert et al 2021).[3] Since the official definition of continuing vocational training by Eurostat encompasses this type of learning (Eurostat 2022), this body of literature implies that interest in online CVT should have increased in the short and medium term.

Second, parents continued to struggle with school and kindergarten closures and their children's periods of quarantine. These additional responsibilities for childcare and homeschooling left less time for CVT. This mechanism implies a declining interest in (online) CVT.

Third, the number of workers reducing working hours due to short-time work allowances[4] increased dramatically in 2020 and 2021, particularly in sectors severely impacted by the pandemic, such as the hotel and restaurant industry (Bellmann et al. 2021). On the one hand, employees may have used the freed-up time for CVT activities, either on their own initiative or that of their employers. On the other hand, companies might have prioritized other aspects, such as addressing a worsening financial situation. Consequently, we cannot conclusively infer whether short-time work allowances are negatively or positively correlated with the interest in CVT.

Fourth, workers worrying about their economic future may have been more concerned with securing income than with investing in qualifications. Literature has well documented that financial constraints such as foregone income and the uncertainty about the benefits of training, are some of the reasons why workers may choose not to participate in training programs (van den Berg et al. 2023). Consequently, workers might have prioritized their current financial situation over investing in future employment opportunities through training due to rising prices in 2022. However, workers who had few opportunities to work in their previous jobs due to social-distancing measures, e.g., artists, may also have seen a need for occupational reorientation, which may again increase the interest in CVT.

In sum, similar to the supply side, the theoretical impact of the pandemic on CVT demand is unclear, but regional differences are likely due to the varying importance of these factors between regions.

3 Related literature

This literature review explores the growing use of Google search data across different fields, particularly its relevance for the evaluation of economic outcomes, including the impact of COVID-19 on educational outcomes. Moreover, we shed light on changes in actual CVT participation with the onset of the pandemic and the adoption of online formats, offering valuable insights into vocational training trends during the pandemic.

The use of Google search data in research has surged over the past decade due to its real-time nature, spanning various fields like IT, communication, medicine, health sciences, business, economics, political science, and sociology (for overviews of the literature see Eichenauer et al. 2022 and Jun et al. 2018). These data are commonly used to monitor trends, to nowcast the current situation, and to forecast future developments. In economics, early papers arose around 2010, (partly) triggered by the intention to explore economic outcomes of the global financial and economic crises from 2007 to 2009 (see Choi and Varian 2012 for a review of the early literature). Google search data has proven to be a good predictor of future unemployment (Askitas and Zimmermann 2010; D'Amuri and Marcucci 2009), inflation (Guzmán 2011), and individual consumption (Vosen and Schmidt 2011). More recently, Baker and Fradkin (2017) showed that Google Trends data is a useful complement to existing measures for aggregate job search activities.

Allowing researchers and policy-makers to track activities in real-time, the current COVID-19 pandemic has caused another surge of papers that try to assess the impact of this crisis on the economy using Google Trends Data. Google data is a good predictor of the economic condition of a region: it is successful in predicting the number of jobs negatively affected by governmental restrictions (Doerr and Gambacorta 2020) and regional unemployment rates (Kong and Prinz 2020). Fetzer et al. (2021) combine Google Trends data with two online experiments and show that economic anxiety, i.e., searches related to the recession, conspiracy, and

[3] Kleinert et al. (2021) conducted an analysis using the German National Educational Panel Study (NEPS) and demonstrated that, especially for professional reasons, online learning through the Internet or apps (such as wikis, online forums, podcasts, or YouTube) became more important in the initial months of the pandemic compared to the period before.

[4] Firms can apply for short-time work allowances when they suffer from a lack of orders and therefore have a surplus in employees. The short-time work program enables firms to temporarily shorten their workers' weekly workings hours, instead of firing them. The Federal Employment Agency pays the allowance as a partial wage replacement for foregone earnings due to smaller working hours (BMAS 2023).

survivalism, increased substantially with the first cases of COVID-19 in the US. These findings from the literature justify our use of Google Trends data not only for mapping training interest but also individual sentiments, such as individuals' economic uncertainty, which is one potential channel of the pandemic's impact on the interest in training as described in Sect. 2.

Further literature analyzing the impact of social distancing measures on educational outcomes supports our hypothesis that interest in online CVT courses might have increased during the lockdowns and that regional differences might matter. School educators, like training providers, were unable to provide face-to-face instructions. Bacher-Hicks et al. (2021) show that COVID-19 increased interest in school- and parent-centered online learning resources due to school closures in the US using Google Trends data. While interest in such topics increased more in regions with high socio-economic standards, suggesting that achievement gaps may widen further in the future, this discrepancy could not be confirmed for Italy, where regions with historically lower academic performance were the ones that searched more for e-learning tools on Google (Amer-Mestre et al. 2021).

Evidence on changes in CVT activities due to the pandemic, particularly in Germany, is based on other data sources. According to the Adult Education Survey, CVT participation continued to increase in 2020, with 60 percent of German inhabitants between 18 and 69 years old participating in some form of training (BMBF 2022). These are 6 percentage points more than in 2018. While 80 percent of the planned CVT activities took place without changes, the average training duration measured in hours decreased from 2018 to 2020 from 46.6 h to 33.5 h. Contrary to that, at the establishment level, Jost and Leber (2021) find a sharp decline in in-company training in 2020 due to economic and financial uncertainties after years of a slow but steady upward trend. Analyzing the IAB Establishment Panel, a survey that has been conducted yearly since 1993, they find that between 2019 and 2020 the number of establishments offering training decreased by almost 40 percent and the number of employees participating in training decreased by almost 60 percent. Particularly affected were establishments with less than 50 employees and entities in sectors that were most affected by the pandemic, i.e., hotels and restaurants. About 56 percent of all establishments reported that they had to cancel planned training activities due to social distancing restrictions, a lack of available instructors, high costs, and economic uncertainties.

COVID-19 further affected the organization of training activities. In 24 percent of the training activities of individuals in 2020, training was affected by newly introduced distance and hygiene rules, and in 15 percent of the cases, training took place online (BMBF 2022). Among formal training courses, online training even accounted for about half of all activities. Among the establishments that did offer training, about half switched to e-learning (Jost and Leber 2021). This is in line with the study by Kleinert et al. (2021), which shows that online learning became especially important for work-related training in 2020. This might not only be due to social distancing measures but also due to the need to close knowledge gaps regarding working with online communication and co-working tools due to working from home.

Overall, the existing literature shows that Google Trends data can be used to map both the interests and sentiments of individuals. The decline in training participation has been accompanied by an increasing share in online training due to social distancing measures and remote collaboration. Our focus in the following study lies in contributing to this research by providing new evidence for the potential impact of the pandemic on workers' interest in training, distinguishing between different waves of COVID-19 infections during the pandemic, potential mechanisms that drive the change in CVT interest, and regional differences.

4 Data

For our analyses, we combine data from different sources: Google Trends data, regional subsidized training data from the Statistical Office of the Federal Employment Agency, and COVID-19 data from the Robert Koch Institute. To distinguish between different phases of the pandemic, we draw on the ZPID lockdown measures data set provided by the Leibnitz Institute for Psychology (Steinmetz et al. 2022), among others.

4.1 Google trends data

Our main outcome measures the search intensity for specific keywords on Google Trends on the most disaggregate level available, i.e., the level of the 16 German federal states. These data are publicly available weekly for the 5 years prior to the moment of retrieval, and monthly since January 1, 2004. They cover the majority of all web search queries in Germany. With a market share of approximately 95 percent in January 2020, Google by and large has been keeping a relatively constant position as the most important search engine in Germany (see Figure 11).

For privacy reasons, Google Trends does not provide actual numbers of search volumes but reports only an index of search volumes that we refer to as search intensities. Google search volumes are relative and not absolute and normalized of the kind

$$\textit{search intensity}_{rt} = \frac{\textit{google searches for keyword}_{rt}}{\textit{total google searches}_{rt}}.$$

Thus, for a given time frame search intensities describe the share of searches devoted to a specific keyword in region r at time t relative to all Google searches in region r at time t. This search intensity scale is then rescaled within a region over a given period such that it takes the value 100 when the keyword has the highest popularity. All other values of search intensities are reported relative to that moment. If a keyword is not searched for enough and falls below a certain, publicly unspecified threshold, the search intensity takes the value 0. The rescaled search intensities allow for a comparison of relative intensities over time within a region. In our regression analyses, we follow a recognized approach in education economics and take the logarithm of the adjusted search intensity values (Bacher-Hicks et al. 2021). This allows us to interpret differences over time as percent changes and simplifies the interpretation of the coefficients.

To avoid biased results in our empirical work, we must account for the data inaccuracies that come along with Google Trends data. The search intensities published by Google are based on a sample of actual searches, not the full number of searches. Data queries for the same keywords and the same region and period made on different days will therefore return different search volume indices (Cebrián and Domenech 2022; Eichenauer et al. 2022; Medeiros and Pires 2021; Rovetta 2021). As Google does not disclose the sampling methods, researchers must account for these inaccuracies, e.g., by taking several requests for the same periods and locations and averaging over the resulting trends. We account for these issues using the average of 14 different requests of weekly and monthly search intensities for the period October 1, 2007 to September 30, 2022 (monthly data) and October 1, 2017 to September 30, 2022 (weekly data) drawn for the Google Trends website between October 7, 2022, and October 22, 2022.

The keywords we investigate are the most common German terms for CVT: "*Weiterbildung*", *"Fortbildung"*, and *"Umschulung"*.[5] To reduce the number of zeros for insufficiently intensive searches on the regional level, we combine search terms with "+" indicating an *„or "*. In detail, we retrieve search information for the following terms: *"Weiterbildung + Fortbildung + Umschulung"* and *"online Weiterbildung + online Fortbildung + online Umschulung"*. This implies that we get the search intensity for searches that include either the term *"Weiterbildung"* or *"Fortbildung"* or *"Umschulung" and ["online" and "Weiterbildung"] or ["online" and "Fortbildung"] or ["online" and "Umschulung"],* respectively. The latter should illustrate if searches for online training became important during our observation period. Based on all this information, we build a monthly data set and a weekly data set on search intensities to look in more detail at the dynamics of search intensity changes.

An important question is which benefits Google Trends data bring to the table compared to more traditional data sources. First, surveys or register data are generally published with time lags of several weeks or months and survey data is usually available only on an annual frequency. Google Trends data, therefore, has some important advantages compared to these traditional data. They are available in real-time and with monthly, weekly, or even daily frequency. Moreover, they can be retrieved for many countries and within countries for regions.

Second, the internet is an integral part of our activities. Individuals collect information online about the goods they intend to buy or about the activities they intend to do. Therefore, web queries might be closer related to intentions and interest in CVT than survey data that ask about workers' sentiments towards training participation. As workers must plan their training activities ahead of time, search queries can be useful leading indicators for subsequent actual training participation. Certainly, younger individuals are more likely to go online than older people. We consider this hardly problematic in our setting, as younger people are more likely to participate in CVT (BMBF 2022) and thus be interested in CVT. However, the specific motivation and intention to enter a specific keyword in a search engine is unclear: do people enter training-related searches because they intend to participate in a training activity, or is this search not directly linked to their personal situation? Several authors have shown that Google Trends data provide an important benchmark and perform better than more traditional indicators, e.g., in the case of private consumption behavior (e.g., Vosen and Schmidt 2011; Woo and Owen 2019). We show that the search intensity for training-related keywords and actual training participation are correlated, by linking available training data with Google data (see Sect. 4.3 for details).

[5] We choose the three terms „Weiterbildung", „Fortbildung" and „Umschulung" because they reflect best the activities that we consider as continuing training. „Weiterbildung " is the generic term for the activity of deepening or supplementing vocational knowledge. This term is used in particular in Social Code—Book III (Sozialgesetzbuch III) when it comes to the continuing qualification of employees and the unemployed. „Fortbildung" is the term used in the Vocational Training Act (Berufsbildungsgesetz) for adaptation and upgrading qualifications aimed at maintaining the ability to act in a given occupation. „Umschulung" refers to intensive training, usually lasting two to three years, with the aim of acquiring a new vocational qualification and is mentioned in both of the above laws.

4.2 Data on non-pharmaceutical measures and COVID-19 incidence rates

On the level of states, we merge additional information from further data sources. To capture the various stages of the pandemic, we merge regional incidence rates from the Corona Data Platform, which provides official numbers on COVID-19 incidences from the Robert Koch Institute (RKI). The RKI is a scientific federal government institution responsible for disease control and prevention in Germany.

Moreover, we retrieve data from the Leibniz Institute for Psychology that collected data on non-pharmaceutical measures taken by the regional German governments to contain the spread of the virus (Steinmetz et al. 2022). This information allows us to picture the intensity of the pandemic in terms of infections and the timing of the individual lockdown periods in the states on a day-by-day basis. Figure 12 in the appendix displays lockdown periods based on the full restriction of selected measures (school closures, prohibition to shop/go to the hairdresser/leave one's home/meet more than one friend/ demonstrate) during the pandemic in 2020 until October 2021. We use this data to compare the lockdown periods with our definition based on similar sources (e.g., Kohl and Denzl 2020). Table 1 provides an overview of the time and the content dimensions of the lockdown phases according to our definition. In most states, the first lockdown in Germany started on March 22, 2020, and ended on May 5, 2020. The second lockdown started in a broader sense on November 2, 2020. Non-pharmaceutical interventions were less drastic than in the first lockdown, but included, e.g., restaurant closures. Measures were tightened again in mid-December (strict contact restrictions, school closures, etc.). We mark the end of the second lockdown in the middle of May 2021, because that is when many regional governments decided on gradual relaxations under certain conditions.

To explore the correlation between the COVID-19 pandemic and search intensities for CVT, we map 7-day incidence rates of COVID-19 infections (calculated as the sum of all infections within seven days divided by the population size) and the weekly search intensities for each state side-by-side in Fig. 2. The red-shaded areas indicate periods with hard lockdowns and the blue-shaded areas indicate periods during the pandemic when there was no lockdown. The first lockdown in March 2020 involved a clear decline in the CVT search intensity in almost all states, although incidence rates were much lower than in the subsequent winter of 2020/21. The second sharp drop took place during the second lockdown in December 2020 in many states. Overall, the figure suggests that search intensities for CVT decreased at least temporarily during the pandemic, especially during lockdowns and when incidence rates were high.

4.3 Linking data on training interest and inflows to subsidized training

One crucial assumption for the value-added of our analysis is that the search intensities from Google Trends are correlated with actual training participation. To test this assumption, we retrieve further data from the Statistical Office of the Federal Employment Agency (FEA). Besides numbers on regional unemployment rates, the FEA provides information on inflows to publicly subsidized training for unemployed and employed workers. Even though the latter quantifies a very particular set of training activities, they have the advantage that they are available from administrative registers every month. By contrast, numbers for general training are not available at this level and are usually based on survey information.

Figure 3 displays the correlation between the share of unemployed starting training in all unemployed and the monthly search intensity for training-related keywords by federal state between January 2018 and June 2021. A purely visual analysis suggests that both variables seem strongly correlated. Table 2 shows the results from additional estimations that regress CVT search intensity from Google data on entries into subsidized training. We find a positive and statistically significant coefficient for a simultaneous relation and lagged search intensity by one month. For lags further back in time we can no longer observe statistically significant correlations. This result might reflect the practical handling of subsidized training provisions in local employment agencies. Individuals receive a voucher for training from their employment agency, which they usually have to redeem rather quickly, i.e., within three months, at a training provider.

5 Empirical strategy

We apply an event-study approach to identify changes in the search interest for training. As noted above, the observation window for the monthly data runs from January 2011 to September 2022. Due to data restrictions, the observation window for the weekly data is shorter and runs from the first week of January 2017 to the last week of September 2022. Figure 4 below illustrates how we model the dynamics in CVT search interest over time.

Our main specification is accordingly:

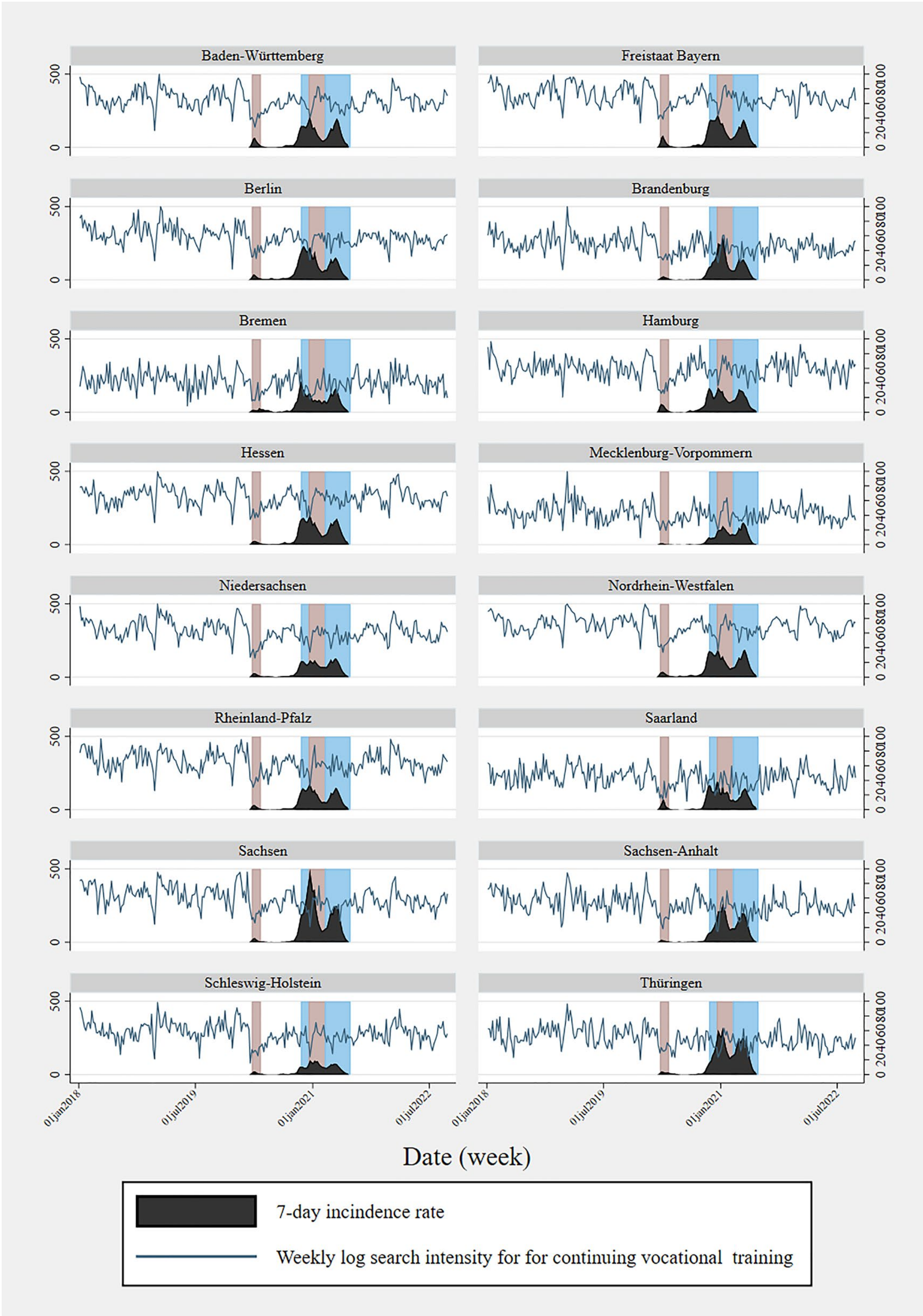

Fig. 2 7-day-incidence rates and log CVT search intensity by federal state

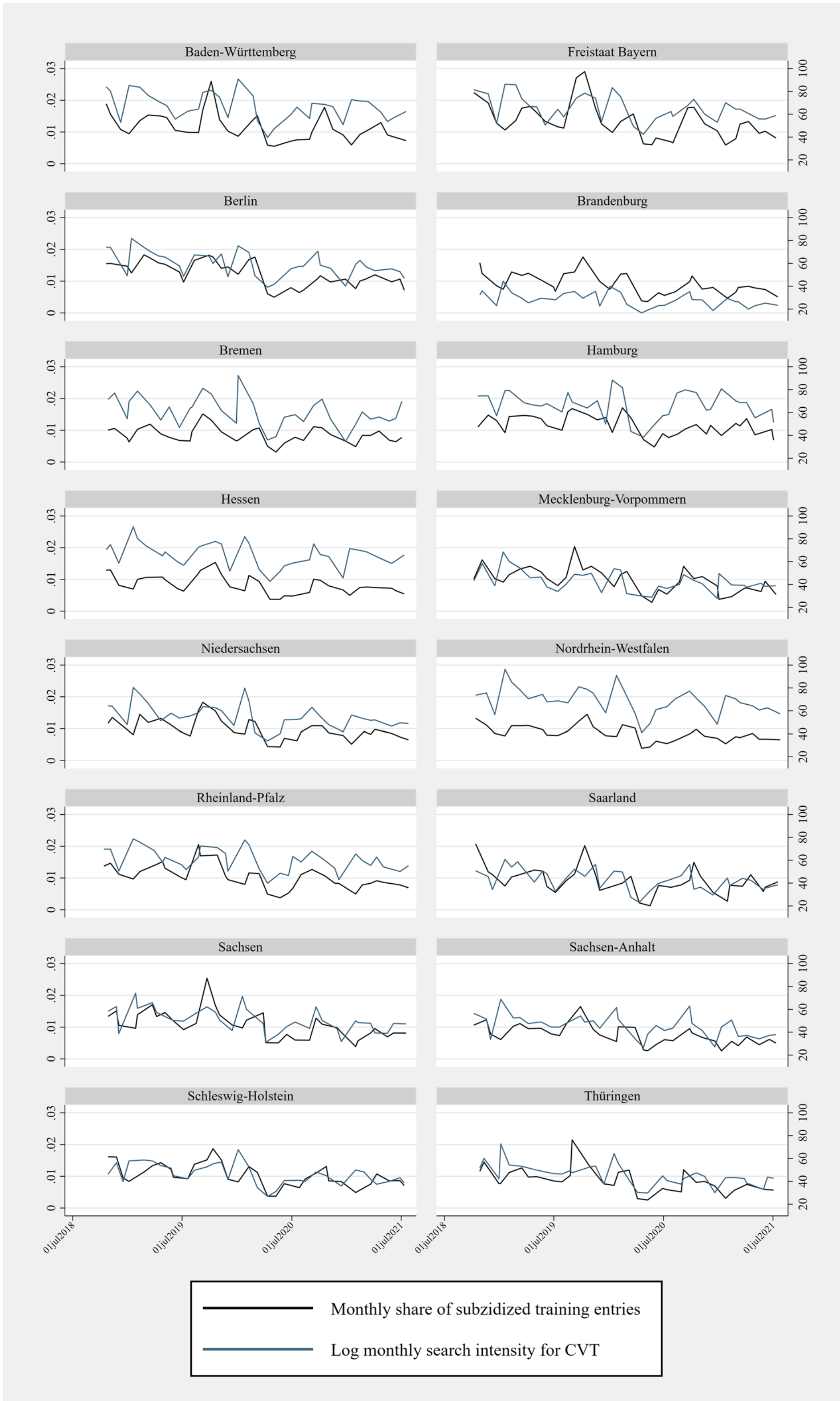

Fig. 3 Correlation between log CVT search intensity and subsidized training intensity for unemployed workers

Table 2 Correlation between log CVT search intensity and subsidized training intensity for unemployed workers

	Model 1	Model 2: lagged search intensity
Search intensity	0.007*** (0.001)	0.005*** (0.001)
Search intensity L1		0.004*** (0.001)
Search intensity L2		0.001 (0.001)
Search intensity L3		– 0.000 (0.001)
N	528	528

Dependent variable: share of entries into subsidized training in all unemployed within a region between January 2018 and June 2021. Model 1 and 2 include the following variables: calendar effects, state FE. Standard errors are in parentheses. ***/**/* indicate statistical significance at the 1/5/10% level

$$
\begin{aligned}
&log\left(search\ intensity\right)_{rt}\\
&\quad = \sum\nolimits_{t=-s'}^{-1} \beta_t\, before_t + \sum\nolimits_{t=1}^{s''} \beta_t\, after_t \\
&\quad + \alpha PriorYears_t + \delta_{m/w(t)} + \theta_{y(t)} + \mu_r + \epsilon_t
\end{aligned}
\tag{1}
$$

We regress the logarithm of search intensity for our training-related keywords in federal state r in month (week) t on a number of month (week) indicators. Here, t indicates the event month (week), which identifies one of the 67 months (194 weeks) relative to February 2020 (the 2nd week of February 2020). Thus, our reference month or week marks a point in time before COVID-19 was recognized as a general health threat by the society and first

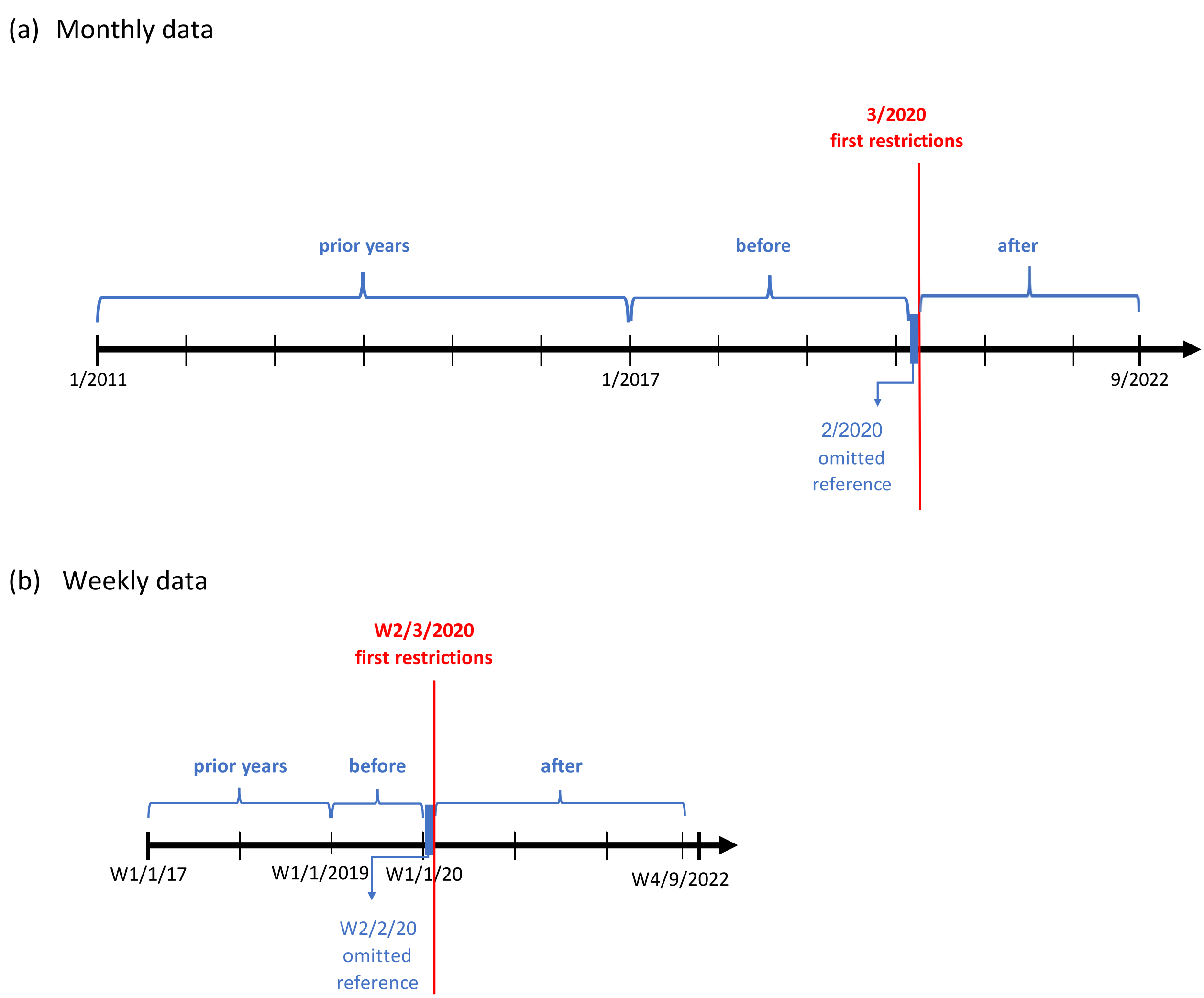

Fig. 4 Modelling CVT search intensity over time using monthly (**a**) and weekly data (**b**)

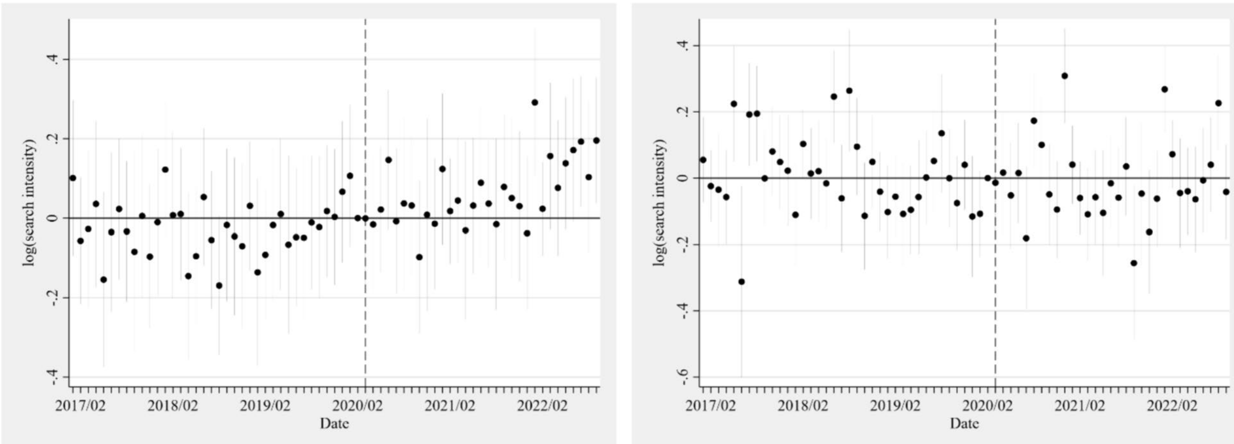

Fig. 5 Event study coefficients for monthly log search intensity for the keywords toothache (Zahnschmerzen) (left) and Mozart (right). Source: Google Trends (2022). Own calculations. Toothache: N = 2,232, Mozart: N = 2254

government measures were installed. *before* is an indicator for s' = 36 months (s' = 57 weeks) falling before that reference point; *after* is an indicator for s" = 31 months (s" = 137 weeks) falling after that reference point. $\delta_{m/w(t)}$ are dummies to capture calendar month (week) effects, $\theta_{y(t)}$ are dummies for calendar year effects, and μ_r are dummies for the 16 federal states.

Because COVID-19 spread everywhere and all 16 states ordered lockdowns more or less at the same time, treatment takes place at the same time across all observational units and we lack a never-treated control group. Therefore, we mainly exploit variation in training-related search intensities over time to examine the pandemic's potential impact on our outcome variables. We solve the underidentification problem of our model, by binning all months (weeks) between the start of our observation window and -s' in the indicator *PriorYears* (Schmidheiny and Siegloch, 2019). This enables us to separate the dynamic effects from time trends. For the monthly data, we observe *PriorYears* from 2011 to 2016. For the weekly data, we observe *PriorYears* from 2017 to 2018.

To estimate average effects of the two specific lockdown periods, we additionally run before-after estimations with two and five periods. The first specification includes a dummy variable *Post* for all months (weeks) from March (22,) 2020 to September (30,) 2022. This gives us an overall average effect of the pandemic on training search intensity:

$$\begin{aligned} &log\left(search\ intensity\right)_{rt} \\ &= \beta_1 Post_t + \delta_{m/w(t)} + \theta_{y(t)} + \mu_r + \epsilon_t. \end{aligned} \tag{2}$$

The second specification distinguishes between the first and second lockdown and the periods in between and after the second lockdown:

$$\begin{aligned} &log\left(search\ intensity\right)_{rt} \\ &= \beta_1\, Lockdown1_t + \beta_2\, between\ Lockdowns_t \\ &+ \beta_3\, Lockdown2_t + \beta_4\, afterLockdown2_t + \\ &+ \delta_{m/w(t)} + \theta_{y(t)} + \mu_r + \epsilon_t. \end{aligned} \tag{3}$$

We include dummy variables to measure effect differences between the first (*Lockdown1*) and second lockdown (*Lockdown2*) and the periods during the pandemic without such strict non-pharmaceutical measures (*betweenLockdowns* and *afterLockdown2*). Again, we use both monthly and weekly data for our analyses.

Our analyses are based on the assumption that increases in the search intensity of a specific keyword correspond to an increase in absolute Google searches for that keyword and that the volume of Google searches did not change due to the pandemic. We try to support this claim by reporting exemplary search intensities that remain consistent over time for keywords that should not have been affected by the Coronavirus outbreak. For this purpose, we chose the two keywords "toothache" ("Zahnschmerzen") and "Mozart". Figure 5 illustrates the search intensities over our observation window. Overall, the search intensities for these crisis-neutral keywords remain constant without any pattern over the entire period. This suggests that the relative importance of these keywords has remained constant compared to the search volume as a whole.

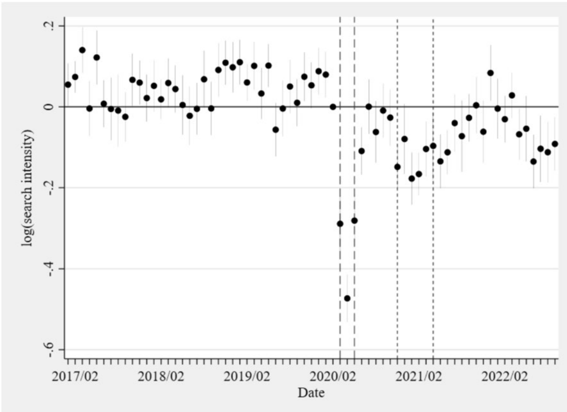

Fig. 6 Event study coefficients for monthly log CVT search intensity. Source: Google Trends (2022). Own calculations. N = 2256. Dashed lines mark the first and second lock-down during the Corona pandemic

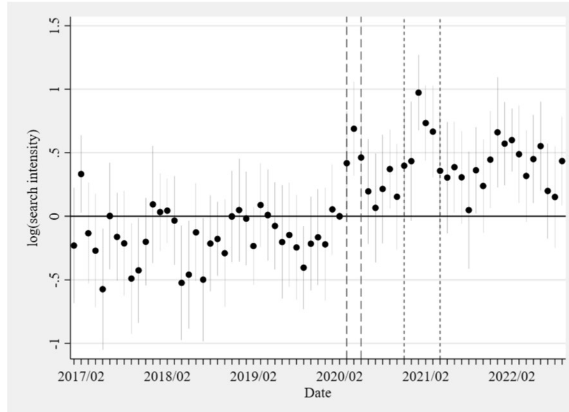

Fig. 7 Event-study coefficients for monthly log search intensity for online CVT. Source: Google Trends (2022). Own calculations. N = 1686

6 Results

6.1 Baseline results

Our first step is to examine whether the pandemic and the accompanying measures had any impact at all on the search intensity for training. Figure 6 shows the results from Eq. (1) of our event study approach. Recall that the reference point is February 2020. The start and end dates of the first and second lockdown are marked by dashed lines. Before March 2020, there is relatively little variation in search intensities. With the onset of the COVID-19 pandemic, however, there is a very sharp drop in searches for CVT. The search intensity decreases by 28.9 percent in March 2020 compared to the previous month. April 2020 was the first month that was completely affected by the lockdown. The search intensity for training dropped by approximately 47.3 percent compared to February 2020. In May, the first restrictions imposed under the lockdown were relaxed (e.g. emergency care in schools and kindergartens was expanded; stores, restaurants, cultural institutions, and also training providers were gradually allowed to reopen subject to distance and hygiene requirements) resulting in a re-normalization of training-related searches. With low numbers of infections, training search intensities were statistically insignificant from pre-pandemic figures during the summer. In the fall of 2020, and especially with the onset of the second lockdown in November/December, the numbers dropped again by more than 17 percent compared to February 2020. Afterwards, the numbers recovered and reached the pre-crisis level again in the fall/winter of 2021. However, the recovery of the interest in training to pre-COVID levels lasted only shortly. The energy crises in 2022 induced by the Russian attack on Ukraine resulted in a renewed drop in training interest, a likely reason being that many individuals were again confronted with economic uncertainties. Figure 13 in the Appendix shows the results for the same model with weekly data, confirming by and large the results from our monthly analysis.[6]

One of the main reasons for the sharp decline in searches for CVT could be that personal face-to-face training was not possible during the lockdowns. Therefore, we also investigate how the pandemic affected the interest in online training courses, which may have been an alternative to classroom training. Note that the search for the three CVT keywords also includes searches for online training terms. Thus, the online training terms are a subset of the general training search terms. Figure 7 shows that interest in online CVT strongly increased during the pandemic. Right at the beginning of the pandemic in April 2020, searches for online CVT increased by 68.9 percent compared to February 2020. The peak value is reached in January 2021 with an increase of 97.3 percent compared to February 2020. Throughout our observation period, the search intensity remains significantly above the pre-crisis level. Again, the pattern looks very similar when we use weekly instead of monthly data (see Figure 15 in the Appendix).

The results are confirmed by the before-after regressions (Eqs. (2) and (3)) presented in Table 3. Including a dummy variable for the whole period of the pandemic from March 2020 to September 2022 (*Post*), we find for

[6] In a robustness check we extend the search to further keywords for CVT: in addition to "Weiterbildung", "Fortbildung" and "Umschulung" we use the keywords "Lehrgang" and "Schulung". The results can be found in Figure 14 in the Appendix.

Table 3 Linear regression results of before-after models—average marginal effects on log search intensity for CVT and online CVT

	Monthly data				Weekly data			
	CVT		Online CVT		CVT		Online CVT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	− 0.189*** (0.020)		0.451*** (0.099)		− 0.121*** (0.021)		0.394*** (0.068)	
First lockdown		− 0.390*** (0.023)		0.611*** (0.127)		− 0.431*** (0.029)		0.478*** (0.089)
Between first and second lockdown		− 0.063*** (0.019)		0.303*** (0.111)		0.009 (0.021)		0.333*** (0.074)
Second lock-down		− 0.162*** (0.026)		0.425*** (0.161)		− 0.114*** (0.027)		0.346*** (0.096)
After second lockdown		− 0.060* (0.033)		0.148 (0.195)		0.009 (0.034)		0.231* (0.123)
N	2,256	2,256	1,686	1,686	4,176	4,176	2,503	2,503

Source: Google Trends (2022). Own calculations. All models include the following variables: calendar effects, state FE. Standard errors are in parentheses. The number of observations for online CVT is lower than for general CVT because in some regions the numbers were not reported in Google Trends at some points in time due to too few search queries. ***/**/* indicate significance at the 1/5/10% level

the monthly data that the search intensity for training decreased on average by 18.9 percent. For the weekly data, the results show that the search intensity decreased on average by 12.1 percent (see columns (1) and (5) in Table 3).

As expected, Fig. 6 shows that search intensity decreased primarily during the lockdowns. Estimating Eq. (3), we take this into account by using two dummies for the periods with lockdowns, and two dummies indicating the period between the two lockdowns and the period after the second lockdown. The results based on the monthly data in Table 3 indicate that the decline in interest in CVT was strongest during the first lockdown when the search intensity decreased on average by 39.0 percent. During the second lockdown, the effect was less than half as large as the one during the first lockdown with 16.2 percent. In the periods during the pandemic when there was no lockdown, the decline in interest in CVT was small, about 6 percent (see Table 3, column (2)). The results with weekly data point in a similar direction (see Table 3, column (6)), although the effects between and after the lockdown are close to zero and statistically insignificant. For online training (Table 3, columns (3), (4), (7), and (8)), the before-after analysis shows that the overall effect of the pandemic on the interest in online CVT is very strong with+45.1 percent (monthly data) and+39.4 percent (weekly data) and was highest during the lockdowns.

6.2 Potential channels for the change in CVT search intensity

In Sect. 2, we delved into the potential mechanisms of the pandemic on the interest in CVT that we derived from the existing empirical evidence. To gain a more comprehensive understanding of demand-side channels, we again turn to Google Trends data to test these mechanisms. We illustrate the changes in search intensity for keywords that may reflect various channels during the pandemic, much like the Figs. 6 and 7, employing the event study approach.

To gauge the increasing digitization and changes in the use of video conferencing tools (VCT) that potentially increase the demand for online training, we analyze the combined search interest for the keywords "Zoom+Skype+WebEx+Microsoft Teams". Contrary to that, we assume that the interest in (online) training decreases due to school/daycare closures that restrict the time of families with children. To measure this, we consequently draw search queries for the keyword "Notbetreuung" (emergency daycare). We further consider two ambiguous channels for (online) training. First, to analyze the importance of short-time work allowances as an ambiguous channel for (online) training (less training initiatives on the firm level vs. freed-up time for workers and more individual-initiated training interest) we draw search queries for the term "Kurzarbeit" (short-time work). Second, we assume a shift in

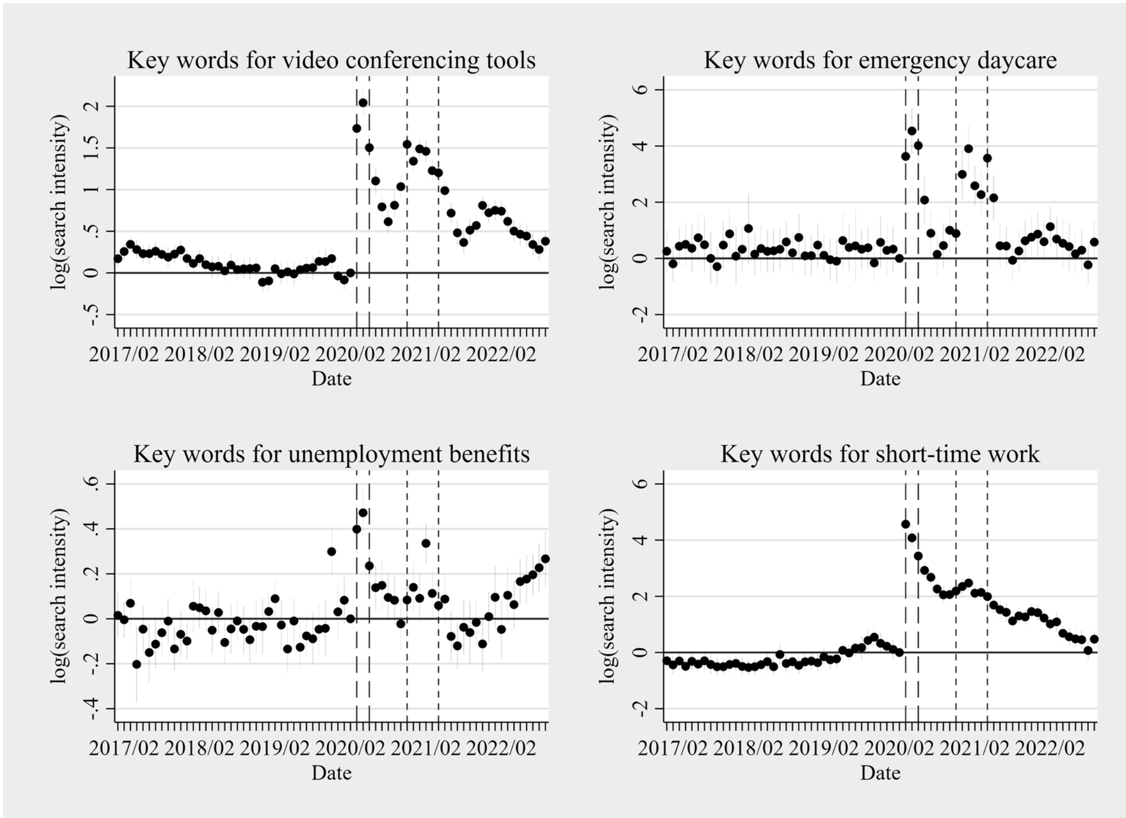

Fig. 8 Event-study coefficients for monthly log search intensity for different keywords. Source: Google Trends (2023). Own calculations. Video conferencing tools: N = 2121, emergency daycare: N = 697, unemployment benefits: N = 2114, short-time work: N = 1908

training-related preferences due to economic insecurities and financial concerns which we try to capture with search queries for "ALG+Grundsicherung" (unemployment benefits and welfare benefits).

Figure 8 shows the development of the search interest for these keywords. It is worth noting that some keywords lack sufficient observations in the Google Trends data due to a lack of search queries in certain regions at certain months. This is particularly true for "emergency daycare," which before the pandemic was mainly relevant during strikes or sickness periods of kindergarten staff. Table 4 depict the corresponding regression results.

According to Fig. 8, all four channels could potentially be relevant, as search queries for all keywords surged with the onset of the pandemic, especially during the lockdown periods (indicated by dashed vertical lines).

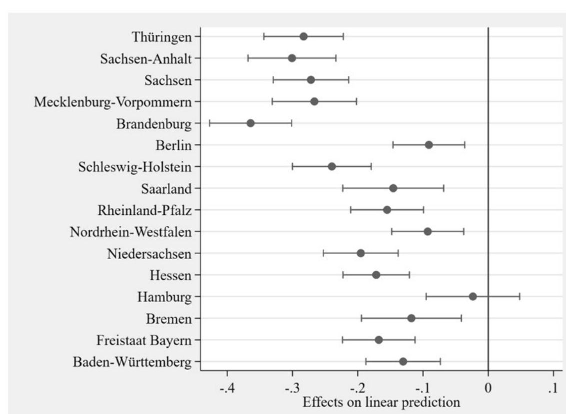

Fig. 9 Average marginal effects of *post* on log CVT search intensity by states. Source: Google Trends (2022)

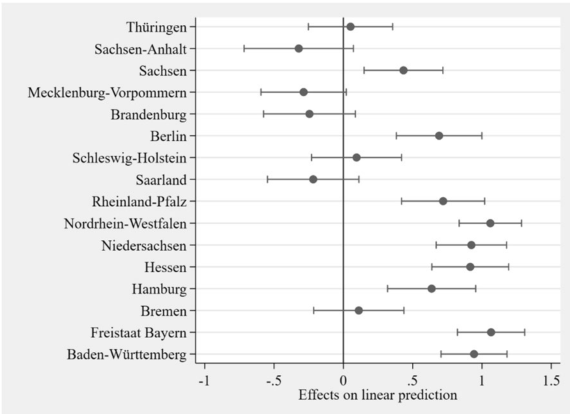

Fig. 10 Average marginal effects of *post* on log search intensity for online CVT by states. Source: Google Trends (2022)

To quantify the correlations between these channels and search intensity for CVT, we extend our regression models (2) and (3) and subsequently add controls for the potentially mediating channels. In addition to using search intensities reflecting these channels, we also include data on actual monthly unemployment and short-time work rates. However, the above channels cannot be interpreted as causal, as there are many factors that have been affected simultaneously with the onset of the pandemic. In section A of the appendix we provide the full regressions results and corresponding discussion.

6.3 Regional differences in the impact of the pandemic

To gain more insight into how regional differences during the pandemic affected interest in CVT, we conduct further analyses. Figure 2 had shown that COVID-19 incidence rates varied a lot in German regions over time. In order to determine possible regional differences, we estimate Eq. (2) (Table 5) and additionally interact the Post dummy with all state dummies.

Figure 9 shows the differences in the effects of the pandemic (Post = 1) on the search intensity for training across states. Noticeably, the effects vary, with the exception of Berlin, with a particular decline in search intensity in the eastern German states (Thüringen, Sachsen-Anhalt, Sachsen, Mecklenburg-Vorpommern, Brandenburg). Figure 16 in the Appendix additionally depicts the pre-pandemic average search intensity levels by state, revealing existing disparities. A similar picture is observed in the pre-pandemic search intensity for online training, which also differed across the federal states (Figure 17 in the Appendix). Figure 10 further illustrates the positive, but sometimes statistically insignificant effects of the pandemic on online training search intensity in western states and the mostly statistically insignificant correlation in eastern states.

The eastern German states have some similarities that may offer explanations for the heterogeneity of the pandemic's effects on interest in CVT. First, there are structural differences in the economy that are associated with a persistently weaker economic situation in eastern Germany (Ragnitz et al. 2019) which may affect training decisions. Moreover, the labor force participation of mothers is higher in eastern states of Germany (Barth et al. 2020) as is the childcare rate (Statistisches Bundesamt 2023), due to differences in socialization with regard to the distribution of tasks between the sexes. Thus, east Germans may have been more strongly affected by closed kindergartens and homeschooling.

Additional analyses reveal that the disparities in the effects by states vary across different phases of the pandemic (see Figure 18 in the Appendix). In the initial lockdown, when limited information about COVID-19 and the pandemic was available and all aspects of life were in a state of emergency, it is unsurprising that all regions experienced a similar decline in interest in training. However, during the second lockdown, we find particularly strong negative effects of the pandemic on interest in CVT for east German states. This trend persisted in the phases between and after the lockdowns, with the negative effect more pronounced in these federal states than in western Germany. While the second wave of Covid-19 infections heavily impacted eastern German states (see Fig. 2), we have no explanation for the persisting negative effect after the second lockdown.

7 Conclusions

In this paper, we analyzed the effect of the COVID-19 pandemic on people`s interest in training using Google Trends data. Even though these data have some limitations, they are particularly advantageous in very dynamic situations–like the COVID-19 pandemic or the most recent energy crisis triggered by the Russian war of aggression–because they can depict developments in real time and accurately to the day.

Analyzing monthly search data, we find that during the first 2.5 years of the pandemic, searches for continuing vocational training strongly decreased on average by

19 percent. While during the first lockdown the decline in the interest for CVT was similar across all German regions (− 39 percent on average), during the second lockdown especially eastern German regions experienced a decrease in searches for CVT. At the same time, the interest in online training strongly increased (+45 percent), especially during the lockdowns when face-to-face training courses were prohibited (+61 and+43 percent). Finally, regarding the most recent energy crisis, we see a persistent increase in the interest in online training and the negative effect on CVT continues, but it is less pronounced than during the pandemic.

Our study complements the findings from the Adult Education Survey that CVT participation continued to increase in 2020 by six percentage points, even though it shows that the average training duration decreased from 46.6 h to 33.5 h (BMBF 2022). Moreover, our results align with the findings by Jost and Leber (2021), who find that the number of employees participating in training decreased by almost 60 percent and the number of establishments offering training decreased by almost 40 percent.

The increasing interest in online training is in line with these findings. First, the organization of training activities shifted from face-to-face to e-learning due to social-distancing regulations and the push in digitization (BMBF 2022, Jost and Leber 2021; Kleinert et al. 2021). Second, the above-mentioned reduced initiative for training from employers may prompt workers to take the lead in initiating their own training, contributing to the observed surge in interest in online training. Third, this could be an indication that the pandemic has shifted employer preferences towards supposedly more cost-efficient online training, similar to what is already suspected of firms adopting advanced digital technologies (Brunello et al. 2023).

In our study, we further test the demand-side mechanisms that might drive this decrease in actual training and increase in online training courses. We show that increased online searches for videoconferencing tools, emergency daycare (time constraints on parents as a relevant mediating channel particularly during the lockdowns), and short-time work might have decreased overall interest in continuing vocational training with the onset of the pandemic, while financial concerns might have mitigated this effect and positively affected the interest in training.

Regarding the interest in online training, we find that all four channels appear to contribute positively to the spike in searches for online training with the onset of the pandemic. This shift may be attributed not only to social distancing measures but also to the necessity of addressing knowledge gaps related to online communication and co-working tools arising from the widespread adoption of remote work (Kleinert et al. 2021).

Finally, we analyze whether there are regional differences in the effects of the pandemic on CVT interest. Google Trends data allow us to examine the development of CVT search intensity on the level of federal states. We find that there are significant regional differences, especially between east German and west German states. The most obvious differences among our analyzed channels, and therefore possible reasons to explain these differences, may be the differences in incidence rates during the second lock-down and the differences in the reliance on public childcare facilities, which were temporarily unavailable during the pandemic. Beyond these two channels, there are major structural differences in the economy between the eastern and western German states, especially in the structure of companies (Ragnitz et al. 2019) which could influence lasting differences in the interest in online training.

Although Google Trends data enables us to draw a very detailed picture of changes in the interest in training over time, some questions remain. We cannot use these data, which are aggregated at the state level, to examine which individuals (employees, unemployed, employers, training providers) changed their search behavior on the internet. Many governments see the need for continuing vocational training to counter skills shortages and make employees fit for digitization. To tackle a decreasing interest in CVT in specific regions, future research needs to unravel which groups of people are experiencing this decline and why. Moreover, the mechanisms that we analyze cannot be interpreted as causal channels, as we might omit important variables that might be correlated with both CVT interest and these four mechanisms. Even though we exploit changes in the channels and CVT interest that are induced by some unforeseen shocks (e.g. first lock-down, Russian attack on Ukraine), there are many factors that have been affected at the same time.

Table 4 Linear regression results of before-after models with stepwise inclusion of controls reflecting mediating channels—average marginal effects on log search intensity for different keywords

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)	(8a)	(8b)
	Search intensities for keywords for mechanisms												**Data on administrative values**			
	Baseline		**Video conferencing tools (VCT)**		**Emergency daycare (ED)**		**Short-time work (STW)**		**Unemployment benefits (UB)**		**All mechanisms**		**Short-time work (STW)**		**Unemployment benefits (UB)**	
	CVT	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**	**CVT**	**Online CVT**
Post	− 0.189***	0.451***	0.671***	0.169	− 0.113***	0.325	0.098***	0.131	− 0.386***	− 3.107***	0.458***	− 3.254***	− 0.006	0.058	− 0.325***	0.727***
	(0.002)	(0.099)	(0.076)	(0.365)	(0.027)	(0.215)	(0.031)	(0.166)	(0.078)	(0.357)	(0.167)	(1.027)	(0.028)	(0.145)	(0.031)	(0.193)
VCT			0.159***	0.770***							0.105**	0.537**				
			(0.017)	(0.096)							(0.045)	(0.225)				
Post# VCT			− 0.283***	− 0.211*							− 0.201***	− 0.127				
			(0.023)	(0.115)							(0.050)	(0.242)				
ED					0.011	0.230***					0.017	0.067				
					(0.010)	(0.054)					(0.011)	(0.073)				
Post# ED					− 0.054***	− 0.159***					− 0.035***	− 0.120				
					(0.011)	(0.060)					(0.012)	(0.080)				
STW							0.042***	0.201***			0.049**	0.201	0.135***	0.301*		
							(0.008)	(0.050)			(0.023)	(0.133)	(0.027)	(0.167)		
Post# STW							− 0.137***	− 0.093			− 0.094***	− 0.181	− 0.149***	-0.256		
							(0.012)	(0.066)			(0.028)	(0.145)	(0.027)	(0.167)		
UB									0.089***	0.181*	0.068	− 0.174			0.041***	0.193***
									(0.020)	(0.103)	(0.051)	(0.255)			(0.004)	(0.021)
Post# UB									0.045**	0.881***	0.032	0.867***			0.011***	− 0.079***
									(0.020)	(0.086)	(0.033)	(0.215)			(0.004)	(0.016)
Obs	2,256	1,686	2,121	1,552	697	582	1,908	1,512	2,114	1,563	583	496	2,256	1,686	2,256	1,686

Source: Google Trends (2023). All models include the following variables: calendar effects, state FE. ***/**/* indicate significance at the 1/5/10% level. Standard errors are in parentheses

Appendix

See Table 4

A. Regression results for potential channels for changes in CVT search intensity

In addition to the graphical illustration of the changes in potential channels that affect CVT search intensity, we now extend our regression models (2) and (3) and subsequently add controls for the potentially mediating channels. Besides using the search intensities for keywords that could reflect the potential channels, for unemployment and short-time work we can additionally support our findings with administrative data. For that purpose, we use on the monthly unemployment rate and the monthly short-time working rate at the federal state level from the Statistical Office of the Federal Employment Agency.

First, the regression results in Table 4, columns 2a and 2b, indicate a positive correlation between the search for video conferencing tools and (online) training interest before the pandemic. After the onset of the pandemic, searches for videoconferencing tools continue to correlate positively with online training, but not with training in general. We find that a doubling of searches for VCT tools is associated with an increase in online CVT searches of around 39 percent (=(0.67–0.28)*100). Moreover, the *Post* coefficient in column 2b becomes smaller and statistically insignificant (0.169 versus 0.451***), confirming that the increase in online training interest might be partly driven by more searches for videoconferencing tools. The results confirm our hypothesis that the spiking interest in videoconferencing tools is correlated with an increasing interest in online training, but not our hypothesis that it increases interest in training in general.

Second, the regression results in Table 4 show that an increase in emergency daycare is associated with less interest in training (− 0.054***). Moreover, the *Post* coefficient in column 3a shrinks from about − 0.189*** to − 0.113*** when we add the interacted control, indicating that part of the drop in CVT search interest is driven by the increasing interest in emergency daycare. However, the results in column 3b indicate that parents with time constraints seem to drive some of the positive impact on online training searches, also after the start of the pandemic. Thus, we find that pandemic-induced time constraints of parents partly drive the decrease we find in training interest, but also the increase we find in online training interest.

Third, Table 4 indicates that more interest in short-time work came with a decrease in training interest, as we obtain a slope coefficient of − 0.095 (=− 0.137***+0.042***) and a *Post* coefficient that becomes less negative (in fact even positive). Thus, the results suggest that lower training initiatives of firms receiving short-time work allowances might be the predominant negative channel of short-time work on training interest. By contrast, the increasing interest in short-time work is weakly positively correlated with online CVT. If the actual short-time work rate is used instead of the searches for short-time work, a similar pattern emerges (see columns 7a and 7b in Table 4).

Fourth, the regression results in Table 4 reveal a positive correlation between economic insecurities and the search for CVT already before the pandemic, and this relation becomes even stronger with the onset of the pandemic. This implies that the as yet ambiguous channel might be such that individuals with financial concerns, for example, because they have fewer opportunities to work in their previous jobs due to social-distancing measures, saw the need to re-orientate or at least upgrade their skills. This channel mitigates other negative pandemic impacts on training interest, which would have been more negative had people not faced economic uncertainties (− 0.386*** versus − 0.189***). This positive impact is even more pronounced for online training (column 5b). This result should be viewed with caution, as the estimates with actual unemployment data point in the opposite direction (column 8b).

In sum, we find that increased searches for videoconferencing tools, emergency daycare, and short-time work decreased overall interest in continuing vocational training with the onset of the pandemic. Only financial concerns mitigate this effect and positively affect the interest in training. Regarding the interest in online training, we find that all four channels contribute positively to the spike in searches for online training after March 2020. As before, we must stress that this observed correlation cannot be interpreted as causal because other potentially related variables might have changed simultaneously.

B. Additional figures and tables

See Figs. 11, 12, 13, 14, 15, 16, 17 and 18

See Table 5

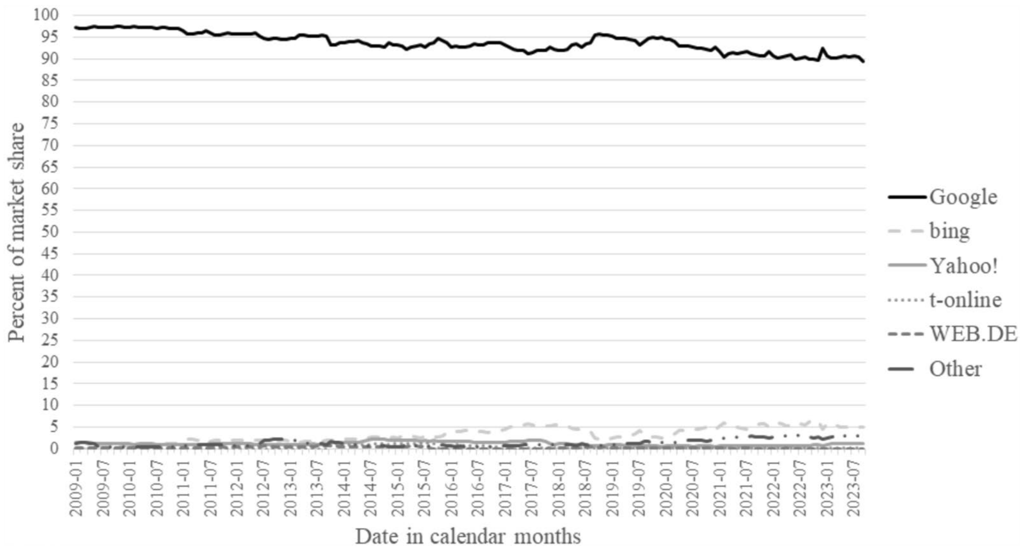

Fig. 11 Search engine market shares in Germany from 1/2009 to 9/2023. Source: The data for this graph are retrieved from StatCounter (2023), licensed under CC-BY-SA 3.0 [https://gs.statcounter.com/search-engine-market-share/all/germany/chart.php?device=Desktop%20%26%20Mobile%20%26%20Tablet%20%26%20Console&device_hidden=desktop%2Bmobile%2Btablet%2Bconsole&multi-device=true&statType_hidden=search_engine&region_hidden=DE&granularity=monthly&statType=Search%20Engine&region=Germany&fromInt=200901&toInt=202309&fromMonthYear=2009-01&toMonthYear=2023-09&csv=1]

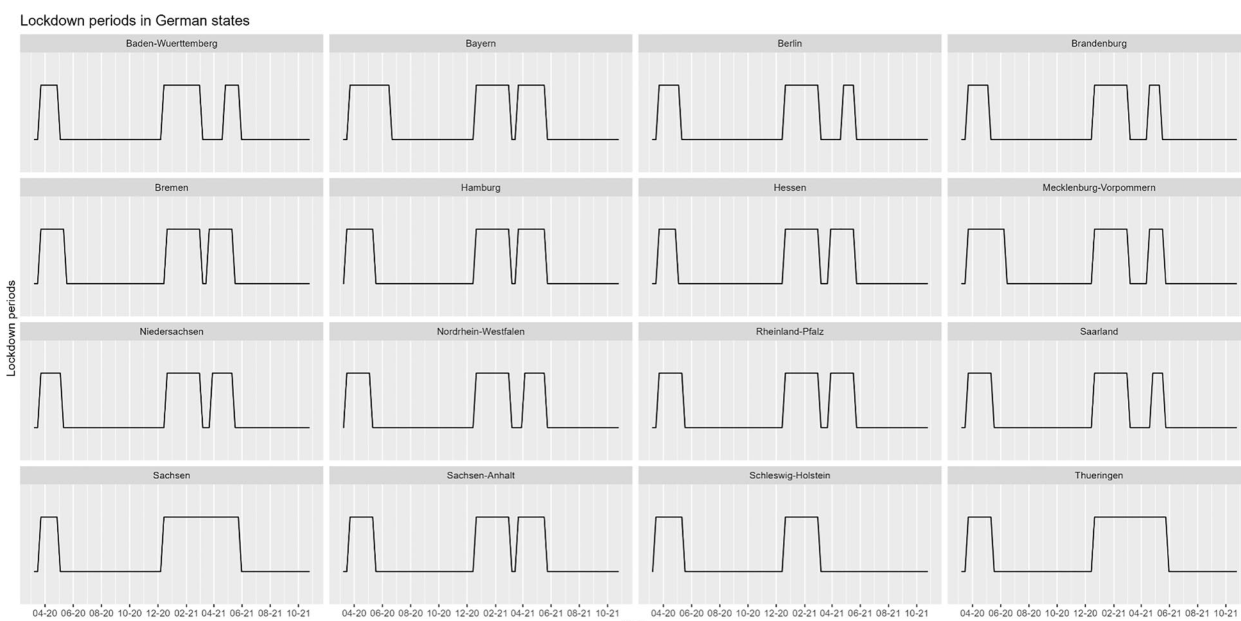

Fig. 12 Lockdown periods by state over time. The ZPID data set classifies overall 16 types of non-pharmaceutical measures into the states "no restrictions", "partial restrictions", and "full restrictions" (Steinmetz et al. 2022). For the definition of lockdown periods in the above figure, we focus on full restrictions of the following measures: school access, shopping, going to the hairdresser, leaving one's home, meeting several friends, right to demonstrate. Source: ZPID lockdown measures data set by the Leibnitz Institute for Psychology (2022)

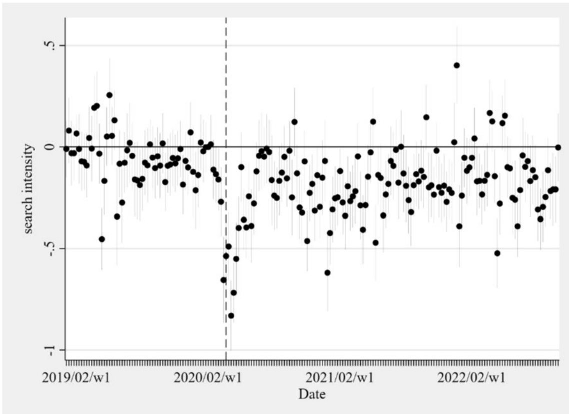

Fig. 13 Event study coefficients for weekly log CVT search intensity. Source: Google Trends (2022). Own calculations. N = 4176

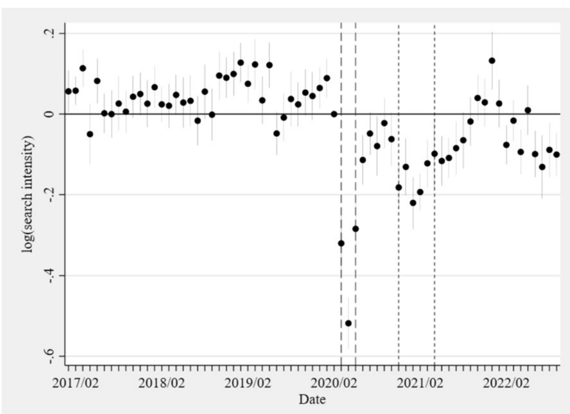

Fig. 14 Event-study coefficients for monthly log search intensity for extended training-related keywords. Source: Google Trends (2022). Own calculations. N = 4176

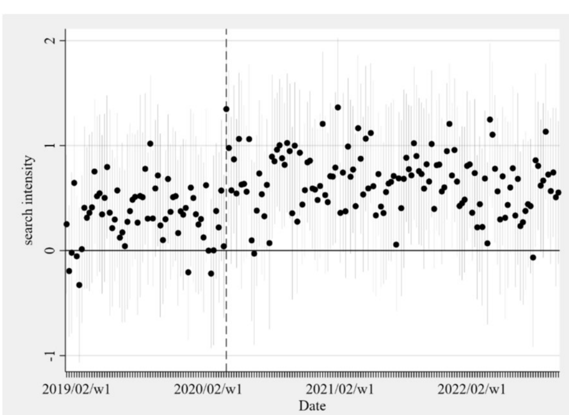

Fig. 15 Event-study coefficients for weekly log search intensity for online CVT. Source: Google Trends (2022). Own calculations. N = 2503

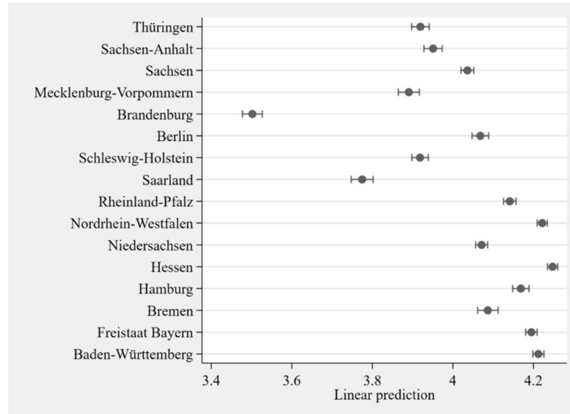

Fig. 16 Average log search intensity levels for CVT by states. Source: Google Trends (2022)

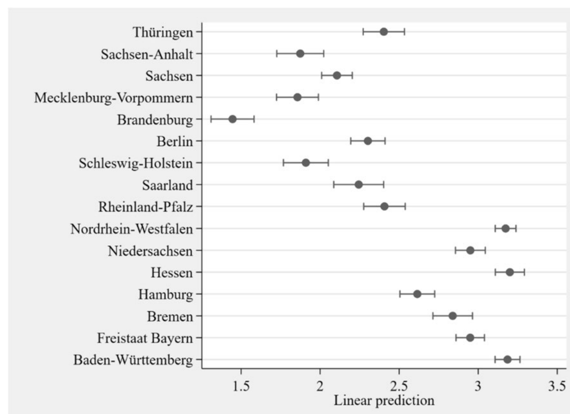

Fig. 17 Average log search intensity levels for online CVT by states. Source: Google Trends (2022)

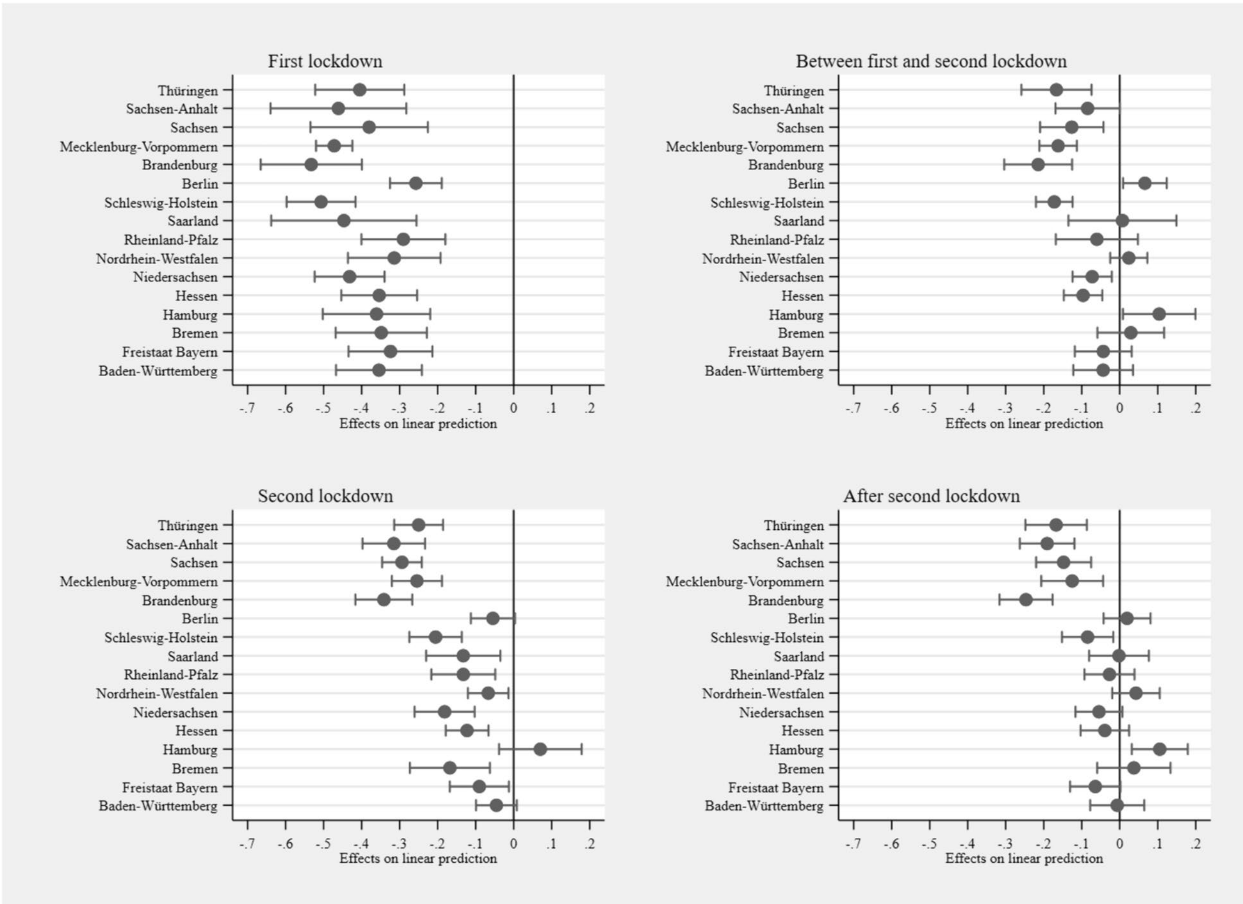

Fig. 18 Average log search intensity levels for CVT by states and periods of the pandemic. Source: Google Trends (2022)

Table 5 Results of before-after models for different regions—effects on log search intensity for online CVT

	Monthly data		Weekly data	
	(1)	(2)	(3)	(4)
Post	0.658*** (0.103)		0.529*** (0.069)	
Post#East	− 0.582*** (0.067)		− 0.402*** (0.048)	
First lockdown		0.885*** (0.126)		0.596*** (0.095)
First lockdown#East		− 0.772*** (0.189)		− 0.343*** (0.116)
Between first and second lockdown		0.495*** (0.122)		0.456*** (0.099)
Between first and second lockdown #East		− 0.536*** (0.149)		− 0.404*** (0.079)
Second lockdown		0.628*** (0.157)		0.488*** (0.099)
Second lockdown#East		− 0.584*** (0.143)		− 0.423*** (0.081)
After second lockdown		0.339* (0.191)		0.360*** (0.124)
After second lockdown#East		− 0.559*** (0.077)		− 0.404*** (0.057)
N	1,686	1,686	2,503	2,503

Source: Google Trends (2022). Own calculations. All models include the following variables: calendar effects, state FE. Standard errors are in parentheses. ***/**/* indicate significance at the 1/5/10% level

Acknowledgements
We thank Sophia Waldmann for her excellent research assistance and two anonymous reviewers for their helpful comments.

Author contributions
Each author contributed significantly to the conception, design, implementation, analysis, and interpretation of the research described in this manuscript. The specific contributions of each author are as follows: Christine Dauth: Conception and Design: Christine Dauth played a central role in formulating the research question and determining the methodology employed. Data Collection: Christine Dauth collected the data from Google Trends via web scraping. She wrote the R data collection protocols and ensured data quality and integrity. Analysis and Interpretation: Christine Dauth conducted first data analysis, employing appropriate statistical techniques and econometric models such as event study analysis. She was responsible for interpreting the results and drawing conclusions from the empirical findings. Manuscript Writing: Christine Dauth played a significantly role in drafting the manuscript, including writing the introduction, literature review, methodology section, and parts of the results and discussion. She contributed to the overall structure, clarity, and coherence of the manuscript. Julia Lang: Conception and Design: Julia Lang actively participated in the conceptualization of the research project. Her expertise on continuing vocational training and labour economics provided valuable insights into the theoretical underpinnings of the research. She collaborated with Christine Dauth to refine the research questions and design an appropriate empirical framework. Data Analysis: Julia Lang conducted the major part of the data analysis, assisted in selecting appropriate econometric models, conducted robustness checks, and explored alternative specifications. Her expertise in statistical analysis enhanced the robustness and reliability of the empirical results. Interpretation and Discussion: Julia Lang played a crucial role in interpreting the empirical findings, placing them in the context of existing literature. She actively contributed to the discussion section, providing insightful interpretations, policy implications, and potential avenues for further research. Manuscript Writing: Julia Lang equally participated in the writing process, making significant contributions to various sections of the manuscript. She was involved in writing the introduction and institutional settings, literature review, the results and discussion, and providing critical revisions for clarity, coherence, and accuracy. Both authors have read and approved the final version of the manuscript and have agreed to be accountable for the accuracy and integrity of the research presented herein. These collaborative efforts demonstrate the joint contribution of both authors to the empirical paper, showcasing their expertise in labour economics and continuing educational training and their commitment to producing high-quality research in the field.

Funding
This research did not receive any specific grant from funding agencies in the public, commercial, or non-profit sectors.

Availability of data and materials
The authors confirm that the data supporting the findings of this study can be made available upon reasonable request.

Declarations

Ethics approval and consent to participate
This study utilized publicly available data from Google Trends and did not involve the collection, use, or analysis of any personal data or personally identifiable information. As a result, ethical approval was not required for this research project.

Competing interests
The authors declare no conflicts of interest that could have influenced the research findings or the presentation of the results in this manuscript.

Received: 11 March 2024 Accepted: 2 July 2024
Published online: 03 August 2024

References

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., Thwaites, G.: Economic uncertainty before and during the COVID-19 Pandemic. J. Publ. Econ. **191**, 104274 (2020)

Amer-Mestre, J., Astigarraga, A., Lopes, M. Academic performance and e-learning in Italy, available at https://www.eui.eu/Documents/Research/New-CMS-research-pages/M-Lopes-et-al-Academic-Performance-and-E-learning-in-Italy.pdf. (2021). Accessed 8 Feb 2022

Askitas, N., Zimmermann, K.: Google econometrics and unemployment forecasting. Appl. Econ. q. **55**(2), 107–120 (2010)

Autor, D.: Why are there still so many jobs? The history and future of workplace automation. J. Econ. Perspect. **29**(3), 3–30 (2015)

Bacher-Hicks, A., Goodman, J., Mulhern, C.: Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time. J. Public Econ. **193**(104345), 1–17 (2021)

Baker, S., Fradkin, A.: The impact of unemployment insurance on job search: evidence from google search data. Rev. Econ. Stat. **99**(5), 756–768 (2017)

Barth, D., Jessen, J., Spiess, K., Wrohlich, K.: Mütter in Ost und West: angleichung bei Erwerbstätigenquoten und Einstellungen, nicht bei Vollzeiterwerbstätigkeit. DIW Wochenbericht **87**(38), 699–706 (2020)

Bellmann, L., Gleiser, P., Kagerl, C., Koch, T., König, C., Kruppe, T., Lang, J., Leber, U., Pohlan, L., Roth, D., Schierholz, M., Stegmaier, J., Aminian, A. Weiterbildung in der COVID-19-Pandemie stellt viele Betriebe vor Schwierigkeiten, In: IAB-Forum 9 December 2020, available at https://www.iab-forum.de/weiterbildung-in-der-COVID-19-pandemie-stellt-viele-betriebe-vor-schwierigkeiten/. (2020). Accessed 15 May 2023

Bellmann, L., Gleiser, P., Kagerl, C., Kleifgen, E., Koch, T., König, C., Leber, U., Pohlan, L., Roth, D., Schierholz, M., Stegmaier, J., Aminian, A. The impact of the COVID-19 pandemic: evidence from a new establishment survey, In: IAB-Forum 26 February 2021, available at https://www.iab-forum.de/en/the-impact-of-the-COVID-19-pandemic-evidence-from-a-new-establishment-survey/. (2021). Accessed 31 Jan 2022

Botha, F., de New, J., de New, S., Ribar, D., Salamanca, N.: Implications of COVID-19 labour market shocks for inequality in financial wellbeing. J. Popul. Econ. **34**(2), 655–689 (2021)

Brunello, G., Rückert, D., Weiss, C., Wruuck, P. Advanced digital technologies and investment in employee training: complements or substitutes? IZA Discussion Paper No. 15936. (2023)

Bundesministerium für Arbeit und Soziales (BMAS) (2023, July 19): Antworten auf die häufigsten Fragen zu Kurzarbeit und Qualifizierung - Was ist Kurzarbeitergeld, https://www.bmas.de/DE/Service/Corona/Fragen-und-Antworten/Fragen-und-Antworten-KUG/faq-kug-kurzarbeit-und-qualifizierung.html. (2023). Accessed 27 Sep 2023

Bundesministerium für Bildung und Forschung (BMBF). Weiterbildungsverhalten in Deutschland 2020—Ergebnisse des Adult Education Survey—AES-Trendbericht, available at https://www.bmbf.de/SharedDocs/Publikationen/de/bmbf/1/31690_AES-Trendbericht_2020.pdf. (2022). Accessed 15 May 2023

Cebrián, E., Domenech, J.: Is Google Trends a quality data source? Appl. Econ. Lett. (2022). https://doi.org/10.1080/13504851.2021.2023088

Choi, H., Varian, H.: Predicting the present with Google Trends. Econ. Rec. **88**, 2–9 (2012)

Christ, J., Koscheck, S., Martin, A., Ohly, H., Widany, S. Digitalisierung—Ergebnisse der wbmonitor Umfrage 2019, Bonn. (2020)

D'Amuri, F., Marcucci, J.: "Google it!" Forecasting the US unemployment rate with a Google job search index, Nota di Lavoro 31.2020. Fond. Eni. Enrico. Mattei. (2009). https://doi.org/10.2139/ssrn.1594132

Dauth, W., Findeisen, S., Südekum, J.: The adjustment of labor markets to robots. J. Eur. Econ. Assoc. **19**(6), 1–50 (2021)

Doerr, S., Gambacorta, L. Identifying regions at risk with Google Trends: The impact of Covid-19 on US labor markets, BIS Bulletin No. 8. (2020)

Eichenauer, V., Indergand, R., Martinez, I., Sax, C.: Obtaining consistent time series from Google Trends. Econ. Inq. **60**(2), 1–12 (2022)

Eurostat. Continuing vocational training in enterprises, Metadata in Euro SDMX Metadata Structure (ESMS), https://ec.europa.eu/eurostat/cache/metadata/en/trng_cvt_esms.htm. (2022). Accessed 15 Sep 2023

Fetzer, T., Hensel, L., Hermle, J., Roth, C.: Coronavirus perceptions and economic anxiety. Rev. Econ. Stat. **103**(5), 968–978 (2021)

Flake, R., Janssen, S., Leschnig, L., Malin, L., Seyda, S. Berufliche Weiterbildung in Zeiten von Corona: insgesamt kein dramatischer Einbruch, aber deutliche gruppenspezifische Unterschiede. In: IAB-Forum, December 1, 2021, available at https://www.iab-forum.de/berufliche-weiterbildung-in-zeiten-von-corona-kein-dramatischer-einbruch-aber-deutliche-gruppenspezifische-unterschiede/ (2021). Accessed 15 May 2023

Genz, S., Janser, M., Lehmer, F.: The impact of investments in new digital technologies on wages—worker-level evidence from Germany. J. Econ. Stat. **239**(3), 483–521 (2019)

Goos, M., Manning, A., Salomons, A.: Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. **104**(8), 2509–2526 (2014)

Guzmán, G.: Internet search behavior as an economic forecasting tool: the case of inflation expectations. J. Econ. Soc. Meas. **36**(3), 119–167 (2011)

Heß, P., Janssen, S., Leber, U.: The effect of automation technology on workers' training participation. Econ. Educ. Rev. **96**, 102438 (2023)

Janssen, S., Leber, U., Arntz, M., Greogory, T., Zierahn, U. Mit Investitionen in die Digitalisierung steigt auch die Weiterbildung, IAB-Kurzbericht 26/2018. (2018)

Jost, R., Leber, U. Die betriebliche Weiterbildung ist in der Corona-Krise massiv eingebrochen. In: IAB-Forum, December 20, 2021. https://www.iab-forum.de/die-betriebliche-weiterbildung-ist-in-der-corona-krise-massiv-eingebrochen/ (2021). Accessed 15 May 2023

Jun, S.-P., Yoo, H.S., Choi, S.: Ten years of research change using Google Trends: from the perspective of big data utilizations and applications. Technol. Forecast. Soc. Chang. **130**, 69–87 (2018)

Kleinert, C., Zoch, G., Vicari, B., Ehlert, M.: Work-related online learning during the Covid-19 pandemic in Germany. Zeitschrift Für Weiterbildungsforschung **44**(3), 197–214 (2021)

Kohl, J., Elisabeth D. Weiterbildungsanbieter in der Corona-Pandemie -Ein erster Blick auf empirische Befunde, Deutsches Institut für Erwachsenenbildung (DIE) (Edts): Krise & Chance, weiter bilden 4/2020, 23–26. (2020)

Kong, E., Prinz, D.: Disentangling policy effects using proxy data: which shutdown policies affected unemployment during the COVID-19 pandemic? J Publ Econ **189**, 104257 (2020)

Lerch, B. Robots and non-participation in the US: where have all the workers gone? Working paper, https://ssrn.com/abstract=3650905 (2022). Accessed 13 Dec 2023

Medeiros, M., Pires, H. The proper use of Google Trends in forecasting models. https://arxiv.org/abs/2104.03065 (2021). Accessed 8 Feb 2022

Nedelkoska, L., Quintini, G.: Automation, skills use and training, OECD Social, Employment and Migration Working papers No. 202. OECD Publishing, Paris (2018). https://doi.org/10.1787/2e2f4eea-en

OECD: Unemployment rate (indicator). OECD, Paris (2021). https://doi.org/10.1787/52570002-en

Ragnitz, J., Rösel, F., Thum, M. Der Graben zwischen Ost und West—welche Politik hilft gegen Ungleichheit?, ifo Schnelldienst, 2019, 72, No. 16, 03–18. (2019)

Rovetta, A.: Reliability of Google Trends: analysis of the limits and potential of web infoveillance duing Covid-19 pandemic and for future research. Front. Res. Metrics Anal. **6**, 1–10 (2021)

Schmidheiny, K., Sieglock, S. On event study designs and distributed-lag models: Equivalence, generalization and practical implications, IZA Discussion Paper 12079. (2019)

Schmidpeter, B., Rudolf, W.-E.: Automatino, unemployment, and the role of labor market training. Eur. Econ. Rev. **137**, 103808 (2021)

StatCounter. Search Engine Market Share Germany Jan 2009—Sept 2023 [graph], available at https://gs.statcounter.com/search-engine-market-share/all/germany/chart.php?device=Desktop%20%26%20Mobile%20%26%20Tablet%20%26%20Console&device_hidden=desktop%2Bmobile%2Btablet%2Bconsole&multi-device=true&statType_hidden=search_engine&region_hidden=DE&granularity=monthly&statType=Search%20Engine&region=Germany&fromInt=200901&toInt=202309&fromMonthYear=2009-01&toMonthYear=2023-09&csv=1 (2023). Accessed 15 Sep 2023

Statistisches Bundesamt. Betreuungsquote von Kindern unter 6 Jahre nach Bundesländern, https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Soziales/Kindertagesbetreuung/Tabellen/betreuungsquote.html. (2023). Accessed 6 Mar 2024

Steinmetz, H., Batzdorfer, V., Scherhag, J., Bosnjak, M.: The ZPID lockdown measures dataset. ZPID Sci. Inf. Online (2022). https://doi.org/10.23668/psycharchives.6679

Tamm, M.: Training and changes in job tasks. Econ. Educ. Rev. **67**, 137–147 (2018)

van den Berg, G., Dauth, C., Homrighausen, P., Stephan, G.: Informing employees in small and medium-sized firms about training: results of a randomized field experiment. Econ. Inq. **61**(1), 162–178 (2023)

Vosen, S., Schmidt, T.: Forecasting private consumption: survey-based indicators vs. Google Trends. J. Forecast. **30**(6), 565–578 (2011)

Woo, J., Owen, A.: Forecasting private consumption with Google Trends data. J. Forecast. **38**(2), 81–91 (2019)

Publisher's Note