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Training during recessions: recent European evidence

Abstract

We use European Union Labour Force Survey data for the period 2005–2018 to investigate the cyclicality of training in Europe. Consistent with the view that firms use recessions as times to update skills, we find that training participation is moderately countercyclical for the employed. Within the not-employed group, this is true also for the unemployed, who are likely to be involved in public training programs during recessions, but not for the inactive, who may be affected by liquidity constraints.

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1 Introduction

What is the expected effect of an economic slowdown on training participation? While several studies investigate the relationship between education and recessions, less is known about training, and what is known mostly refers to US data before the 2009 recession or to apprenticeships in Europe (see Méndez and Sepúlveda, 2012; Muehlemann et al., 2020, and the references therein).

Why should the business cycle affect training? For firms, the forgone production associated with training declines during recessions, inducing them to hoard temporarily idle employees and train them in the expectation that their productivity will be higher when the economy picks up again.[1] This behavior generates countercyclical training. Two other effects, however, push in the opposite direction. First, unemployment rises in a downswing, inducing firms to hire cheaper skilled workers in the market instead of training their employees. Second, since profits decline in downturns, financially constrained firms may cut training expenses. For individuals, the lower opportunity cost of time in a recession increases their incentive to invest in human capital, but liquidity constraints curb it. As a result, it is difficult to establish a priori whether training is counter- or procyclical.

In this paper, we investigate the effects of the business cycle on training participation in Europe by using data from the European Labour Force Survey, which cover 27 European countries and the quarters from 2005Q1 to 2018Q4.[2] When we pool all individuals – employed or not – we estimate that training participation is mildly countercyclical. However, when we distinguish between the employed and the not employed – carefully addressing the self-selection into each sample with an instrumental variable approach – we find that training participation is countercyclical only for the employed, in line with the view that firms and workers use recessions as times to update skills. For the not employed, we find that training is countercyclical for the unemployed, who are likely to be involved in public training programs during recessions, and acyclical for the inactive, who may be hampered by liquidity constraints. We also investigate effects along the intensive margin of training hours and the interaction between recessions and labor market institutions.

The paper is organized as follows. Section 2 provides a review of the empirical literature on the relationship between training and the business cycle, Section 3 introduces the data and the empirical strategy and Section 4 presents the results. Conclusions follow.

2 Literature Review

The empirical literature discussing the relationship between training and the business cycle has so far produced mixed results.[3] Sepúlveda (2004) developed a real business cycle model with employment adjustment costs, labor hoarding, and countercyclical training activities. In a downturn, the foregone production cost of training declines, labor is retained because of the presence of adjustment costs, and training occurs, much in the spirit of Hall's model of organizational capital (Hall, 1991).

1 Labor hoarding is likely to be more pronounced in countries with higher employment protection.
2 This paper draws on previous unpublished work of ours (Brunello and Bertoni, 2021).
3 Closely related to this literature is the one on wage cyclicality. See, for instance, Martins et al. (2012).

Sepúlveda uses data from the US National Longitudinal Survey of Youth (NLSY) to construct a panel of individuals aged 14–22 years in 1979, which he follows until 1998. Focusing on the incidence and intensity of off-the-job and on-the-job training, measured in hours and net of apprenticeships, he reports that they are weakly countercyclical, lead the cycle, and are highly volatile, with a standard deviation of >10 times that of the output.

Majumdar (2007) also uses NLSY data for the period 1979–1988 but finds that the probability of receiving company training decreases when the local unemployment rate increases, which points to procyclical training. This negative association, however, is only statistically significant for workers who have joined the firm since the last wave. Majumdar explains his results as the outcome of two countervailing effects, with the latter dominating the former: on the one hand, labor market opportunities for trained workers are fewer in a downturn, which reduces their bargaining power with the firm and increases the employer's incentive to train. On the other hand, there are many alternatives to training in a slack labor market, which induces firms to hire rather than train.

Bassanini and Brunello (2008) study the relationship between product market regulation and workplace training, using data for 15 European countries and 8 years – drawn from the European Labour Force Survey. They find that their measure of training incidence – the proportion of employed individuals who received training in the 4 weeks before the reference week – is negatively correlated with their measure of the business cycle, the logarithm of worked hours filtered from trend using the Hodrick–Prescott filter,[4] in line with Sepúlveda's findings for the United States.

Felstead and Green (1996) report instead that training was procyclical in Britain during the 1970s, 1980s, and 1990s. Felstead et al. (2012) examine the impact of the 2008–2009 recession on training activity in the United Kingdom. Using data from the National Employer Skills Survey 2009, they show that cuts in training expenditures were not as severe as feared. Although a minority of employers did cut expenditure and coverage as a result of the recession, most reported no significant change, and some had even increased their commitment. Training expenditure in real terms fell by only 5%between 2007 and 2009.

In his review of the literature focusing on apprenticeships, Brunello (2009) concludes that the ratio of apprentices to employees tends to be (mildly) procyclical and to decline during a recession, with the notable exception of the Great Depression, when it rose (at least in England). Recent evidence from Switzerland confirms this assessment (see Luthi and Wolter, 2020). When broader measures of training are considered, which exclude apprentices, the weight of the evidence is in favor of countercyclical training incidence.

More recently, Muehlemann et al. (2020) have used German data on apprenticeships from 2007 to 2019 and information on business cycle expectations up to June 2020 and estimate that the coronavirus-related decrease in firms' expectations about the business cycle is associated with a predicted 8% decrease in firm demand for apprentices and a 6% decrease in the number of new apprenticeship positions in Germany compared to 2019.

Finally, Méndez and Sepúlveda (2012) argue that, in the United States, while aggregate schooling exhibits a countercyclical pattern, the case for countercyclical training is weak at the *aggregate* level. However, when training episodes are decomposed into independent categories,

4 The Hodrick–Prescott filter or decomposition is a procedure that decomposes a time series into its trend and business cycle components.

they highlight two key distinctions: (a) between firm-financed training, which tends to be strongly procyclical, and training financed by the individual, which tends to be countercyclical (see also Alessandrini et al., 2015); (b) between employed and unemployed individuals. Training seems much more procyclical for the former than for the latter.

This paper contributes to this literature in two ways. First, we argue that it is important to distinguish between the employed and the not employed, because firm-sponsored training is mostly undertaken by employed workers and firms are likely to encourage training during recessions. Training by the unemployed and the inactive, instead, may be difficult during recessions, when individuals face liquidity constraints. We estimate the sensitivity of training to cyclical unemployment for the employed and the not employed and explicitly address the endogenous selection of individuals between groups. We show that the cyclical behavior of training participation varies with labor market status. Second, we are the first to investigate the cyclicality of training in a sample that covers all the 27 European member states. We also highlight that the cyclicality of training varies with labor market institutions, such as employment protection, and the importance of public expenditure in training.

3 The Data

We use quarterly data from the European Union Labour Force Survey (EU-LFS), a harmonized household survey that collects information on labor markets across all EU 27 member states. We restrict our sample to the period from 2005 until 2018 to account for the substantial changes in the survey that took place until 2004 and consider individuals aged 25–64 years. Our final estimation sample spans 14 years and 27 countries and counts >43 million observations.

Our key measure of training is training participation (T), a binary variable that is equal to "1" if individuals attended – within the past 4 weeks – courses, seminars, conferences, or private lessons or instructions outside the regular education system and equal to "0" otherwise. We also look at training intensity, measured by training hours during the past 4 weeks. As in Méndez and Sepúlveda (2012), our business cycle indicator is the quarterly country-specific unemployment rate (U), which can be decomposed into a trend component, a cyclical component, seasonal effects, and residual noise.

For each country, we capture seasonality by regressing U on quarter dummies. We then decompose the residuals into a trend (U_trend) and a cyclical component (U_cycle), using the filter proposed by Hodrick and Prescott (1997) and adopting a smoothing parameter of 1,600 (Ravn and Uhlig, 2002). Since training participation T also includes a pronounced seasonal component – its level drops by about 50% during the summer quarter of each year – we filter out this component by retaining the residuals of country-specific regressions of T on quarter dummies. We define these residuals as TR. Descriptive statistics for our final sample are shown in Table 1.

As a preliminary step, we regress both training participation and training hours on gender, age, educational attainment, labor market status, country group, quarter, and year dummies. The results, reported in Table 2, show that both training participation and intensity decline with age and are the highest among the better educated and those who

Table 1 Descriptive statistics

	Observations	**Mean**	**SD**
Participated in training	43,173,984	0.066	0.248
Participated in training – employed	30,372,367	0.079	0.271
Participated in training – not employed	12,801,617	0.034	0.181
Training hours	43,173,984	1.113	9.205
Training hours – employed	30,372,367	1.090	7.664
Training hours – not employed	12,801,617	1.170	12.100
Age (years)	43,173,984	45.38	11.07
Male	43,173,984	0.486	0.500
Has a tertiary education degree or higher	43,173,984	0.249	0.432
Employed	43,173,984	0.703	0.457
Unemployment rate – cyclical component	1,620	0	1.128
Unemployment rate – trend	1,620	0.092	0.041
Employment rate – cyclical component	1,620	0	0.994
Employment rate – trend	1,620	0.643	0.059

Table 2 Descriptive analysis

	Training participation	**Training hours**
Gender: male	−0.020*** (0.001)	−0.030*** (0.007)
Age × 10	−0.005*** (0.000)	−0.038*** (0.002)
Upper secondary education	0.008*** (0.002)	0.212*** (0.031)
Tertiary education	0.058*** (0.003)	1.301 *** (0.054)
Not employed	−0.029*** (0.001)	0.645*** (0.047)
Second quarter	−0.001 (0.004)	0.038 (0.084)
Third quarter	−0.028*** (0.003)	−0.367*** (0.073)
Fourth quarter	0.003 (0.004)	0.068 (0.083)
Western and Central Europe	0.051*** (0.003)	1.342*** (0.049)
Southern Europe	0.018*** (0.002)	0.660*** (0.065)
Northern Europe	0.123*** (0.006)	1.783*** (0.120)
Observations	43,173,984	43,173,984
R-squared	0.048	0.011

Notes: Less-than-secondary education, female gender, employed, first quarter, and Eastern Europe are the omitted reference categories.
Standard errors clustered by country and time period are reported in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

live in Northern Europe. While training participation is the highest for the employed, training intensity is the highest among the not employed. Conditional on training participation, the employed have spent during the past 4 weeks 16.85 hours of training on average, while the unemployed and inactive have spent 47.74 hours and 40.26 hours, respectively. The longer duration of training among the not employed may depend on the fact that those out of work need to master new skills, while those at work often need only to upgrade existing skills.

Consistent with the evidence reviewed in Bassanini et al. (2007), we also find that training participation and intensity are higher for females than for males. One reason for this is that we are considering all types of training. If we restrict our attention to the participation in training that takes place during working hours, which is likely to be paid or organized by the employers, this is higher for males than for females.[5]

4 Empirical Strategy

We estimate the following regression model:

$$\mathrm{TR}_{\mathrm{ict}} = \sum_{y} \alpha_y D_y + \sum_{c} \alpha_c D_c + \beta_1 U\_cycle_{\mathrm{ct}} + \sum_{c} \beta_{2c} D_c U\_trend_{\mathrm{ct}} + \gamma X_{ict} + u_{ict}, \tag{1}$$

where $\mathrm{TR}_{\mathrm{ict}}$ is the net of seasonal effects; D_y and D_c are vectors of year and country dummies; $U\_\mathrm{cycle}_{\mathrm{ct}}$ and $U\_\mathrm{trend}_{\mathrm{ct}}$ are the business cycle and trend indicators, and we allow for trend effects that are country specific (β_{2c}); X_{ict} is a set of individual-level controls that include age, gender, and whether the individual has a tertiary education degree or not, and u_{ict} is the error term. We cluster standard errors by country and time period.

We investigate the differential response of training to the business cycle for the employed and not employed by estimating Eq. (1) separately for each group. We address the endogenous selection of individuals into each subsample by augmenting the specification in Eq. (1) with the inverse Mills ratio (IMR), obtained from the estimate of the effects of the explanatory variables in Eq. (1) and the additional variable Z_{ct} on the probability of individual employment, using a probit specification.[6]

The variable Z_{ct} is a proxy of country-specific demand shocks and serves as the exclusion restriction (i.e., an instrumental variable), guaranteeing that our switching regression model is not identified by functional-form restrictions alone. Following the shift-share logic of Autor et al. (2013), we define Z_{ct} as follows:

$$Z_{ct} = \sum_{k} \left[\frac{E_{kt}}{E_{k,t-1}} - 1 \right] \times \frac{E_{ck,\tau}}{E_{k,\tau}}, \tag{2}$$

where $\left[\frac{E_{kt}}{E_{k,t-1}} - 1 \right]$ is the aggregate change in EU-27 employment in industry k between quarters t and $t-1$ and the weights $\frac{E_{ck,\tau}}{E_{k,\tau}}$ are the ratios of industry k workers in country c to industry k workers in the EU-27 area in year τ. This year is 1995 for all countries except the following: Slovenia (1996); Czech Republic, Estonia, Poland, and Romania (1997); Latvia, Lithuania, and Slovakia (1998); Cyprus (1999); Bulgaria (2000); and Croatia (2002).

By combining the predetermined employment shares by industry and country with the aggregate industry-level employment changes in the whole of EU-27, Z_{ct} captures the changes in the employment rate that are not purely explained by country- and industry-specific labor supply shocks. Conditional on country-specific trends and aggregate year effects, it is unlikely that overall EU employment changes directly affect country-specific training. Therefore, the validity of the exclusion restriction relies on the assumption that the presample shares $\frac{E_{ck,\tau}}{E_{k,\tau}}$ can

5 The information on whether training occurs during working hours or not is only available with annual data. For example, when we use the 2016 wave and regress the probability of participating in training exclusively or prevalently during working hours on the same variables used in Table 2, we find that the gender dummy (male =1, female =0) attracts a positive and statistically significant coefficient (0.004, standard error: 0.002).

6 Méndez and Sepúlveda (2012) deal with selection using panel data methods. This approach is precluded here, because our data are repeated cross sections.

be taken as exogenous. Since these shares are computed for most countries between 7 years and 10 years before the start of our sample, we consider this assumption as plausible.

5 Results

5.1 Baseline results

In Table 3, we report the estimates of the effect of the cyclical component of the unemployment rate on individual participation in training. The table has four columns: Column (1) shows the estimated effect of the business cycle indicator *U_cycle* on training for the pooled sample; Column (2) reports the marginal effect of *U_cycle* on the probability of being employed, using a probit specification; Columns (3) and (4) report the estimated effects of *U_cycle* on training for the employed and the not employed, respectively. The *R*-squared values (pseudo-*R*-squared value for the probit in Column (2)), as well as the marginal effects for age, gender, and education, are also reported. The patterns described by these coefficients are in line with the descriptive analysis presented in Table 2.

Table 3 The effects of the business cycle (*U*_cycle) on training participation and employment status

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	**Training participation**	**Employment probability**	**Training participation**	**Training participation**
Sample	**All**	**All**	**Employed**	**Not employed**
Cyclical component of unemployment rate × 10	0.015**	−0.038***	0.024***	0.006
	(0.006)	(0.006)	(0.007)	(0.005)
Demand shock: Z_{ct}		0.007***		
		(0.001)		
Inverse Mills ratio			−0.108***	0.051***
			(0.010)	(0.005)
Male gender	−0.015***	0.140***	−0.045***	0.006***
	(0.001)	(0.002)	(0.003)	(0.001)
Age	−0.001***	−0.008***	0.001***	−0.003***
	(0.009)	(0.001)	(0.001)	(0.001)
Has tertiary education	0.058***	0.154***	0.036***	0.052***
	(0.002)	(0.002)	(0.003)	(0.002)
R-squared	0.076	0.098	0.077	0.062
Observations	43,173,984	43,173,984	30,372,267	12,801,617
Estimation method	OLS	Probit	OLS	OLS

Notes: The table reports the effects of the business cycle on employment and training participation. The dependent variable is listed in the heading of each column. Estimates refer to the full sample in Columns (1) and (2), to the employed in Column (3), and to the not employed in Column (4). Column (2) reports the marginal effects from a probit specification. Each regression also includes year and country dummies and country-specific employment trends. For the probit specification, the pseudo-*R*-squared value is reported instead of the *R*-squared value. Standard errors clustered by country and time period are reported in parentheses. OLS: ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

We find that, in the pooled sample, training participation is moderately countercyclical: a one-standard deviation increase in the business cycle component of the unemployment rate raises training participation by 2.56% of its mean (0.0015 × 1.128/0.066), a statistically significant effect. During the recession of 2009, cyclical unemployment increased on average by 0.471 standard deviations (0.531 percentage points). Our empirical model predicts that training participation increased by 1.21% of its mean (2.56 × 0.471). This finding contrasts with the evidence presented by Méndez and Sepúlveda (2012), who conclude that, for the United States, the case for countercyclical training is weak at the aggregate level.

The probability of individual employment is instead procyclical, as a one-standard deviation increase in the cyclical indicator reduces the probability of individual employment by close to 0.43 percentage points (0.0038 × 1.128). In addition, the demand shock Z_{ct} positively and significantly affects the probability of employment, suggesting that the instrument is relevant (the *F*-statistic is >40).

When we consider the sample of employed and not employed individuals separately, by taking into account their endogenous selection into each group, we find that training is countercyclical for the employed (estimated coefficient of *U_cycle*: 0.0024, standard error: 0.0007) and acyclical for the not employed (estimated coefficient of *U_cycle*: 0.0006, standard error: 0.0005). Based on these estimates, a one-standard deviation increase in the cyclical component of the unemployment rate raises training participation by 3.43% (0.0024 × 1.128/0.079) for the employed but has no statistically significant impact on the participation of the not employed.[7]

The 12,801,617 individuals in our sample who are not employed include 10,175,281 respondents who out of the labor force (79.5%) and 2,626,336 who are unemployed (20.5%). Compared to those out of the labor force, the unemployed are more likely to be males (52.1% vs 33.5%), to be younger (40.9 years vs 49.9 years on average), and to have a tertiary education degree (18.3% vs 13.0%). To understand whether there are differences between these two groups in the responsiveness of training to the business cycle, we drop inactive respondents and reestimate Eq. (1) in the residual sample and separately for the employed and the unemployed. The results – reported in Table 4 – highlight that training participation is countercyclical for the unemployed (estimated coefficient of *U_cycle*: 0.0036, standard error: 0.0008), who are typically involved in activities organized by public employment agencies, including training.

By combining the results in Tables 3 and 4, we also conclude that the major distinction seems to be between the active (employed plus unemployed) and the inactive and not between the employed/unemployed. This finding is confirmed by the results in Table A2 in the Appendix, where we report the effects by labor force participation and show that the effect of *U_cycle* on the inactive individuals is acyclical (with estimated coefficient equal to 0.0005). Training participation is instead countercyclical for both employed and unemployed but presumably for different reasons. On the one hand, employers take advantage of recessions to retrain their employees. On the other hand, labor market policies encourage training of the unemployed during recessions, as eligibility to unemployment benefits is often tied to active participation in labor market programs, including training (Organisation for Economic Co-operation and Development [OECD], 2001).

7 Since the inverse Mills ratio is a generated regressor, one may argue that inference requires bootstrapping. Although bootstrapping with 43 million observations is not computationally feasible for us, we show in Appendix Table A1 that our conclusions are robust when we consider a 5% random sample of the data by country and time period and bootstrap standard errors using 200 replications (clustered by country and time period).

Table 4 The effects of the business cycle (*U*_cycle) on training participation and employment status (excluding the inactive)

	(1)	(2)	(3)	(4)
Dependent variable	**Training participation**	**Employment probability**	**Training participation**	**Training participation**
Sample	**Labor force**	**Labor force**	**Employed**	**Unemployed**
Cyclical component of unemployment rate × 10	0.018**	−0.026***	0.026***	0.036***
	(0.008)	(0.006)	(0.008)	(0.008)
Demand shock: Z_{ct}		0.005***		
		(0.001)		
Inverse Mills ratio			−0.127***	−0.121***
			(0.026)	(0.031)
Observations	32,998,703	32,998,703	30,372,367	2,626,336
Estimation method	OLS	Probit	OLS	OLS

Notes: The table reports the effects of the business cycle on employment and training participation. The dependent variable is listed in the heading of each column. Estimates refer to the labor force in Columns (1) and (2), to the employed in Column (3), and to the unemployed in Column (4). Column (2) reports the marginal effects from a probit specification. Each regression also includes age, gender, a dummy for tertiary education, year and country dummies, and country-specific employment trends. Standard errors clustered by country and time period are reported in parentheses. OLS, ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

The finding that the inactive do not participate more in training during a recession may be explained if they choose to enroll in formal education instead of training. However, when we regress a binary variable equal to “1” for participation in regular education during the past 4 weeks and to “0” otherwise on the cyclical indicator, as well as the controls in Eq. (1), we find that participation by the inactive declines during a business downswing.[8] The fact that, for this group, both training and formal education do not increase during a recession, when the alternative uses of time are reduced, suggests that the presence of liquidity constraints hampers enrollment in both types of activities.

One may wonder whether and how our findings would change if we do not account for the endogenous selection into employment over the business cycle. To investigate this, we report – in Table 5 – the estimates by employment status with and without including the IMR. It turns out that the correction for sample selection makes little difference for the estimated effects, both qualitatively and quantitatively (at the fourth decimal). Given the statistical significance of the IMR, however, it is useful to interpret the observed differences.

The table shows that training participation for the employed is less countercyclical in Column (3) – where the estimates combine selection and causal effects – than in Column (1) – where the selection effect is taken care of by including the IMR. In this case, the selection effect is procyclical: in an economic expansion, some unemployed and inactive move into employment, requiring training. Therefore, training of the employed becomes less countercyclical. The opposite holds for the not employed, as training is more countercyclical in Column (4)

8 The estimated coefficient associated with cyclical unemployment is −0.010 (standard error: 0.003).

Table 5 The effect of selection into employment on the estimates of the effects of the business cycle on training participation

	(1)	(2)	(3)	(4)
Dependent variable	**Training participation**	**Training participation**	**Training participation**	**Training participation**
Sample	**Employed**	**Not employed**	**Employed**	**Not employed**
Cyclical component of unemployment rate × 10	0.024***	0.006	0.017**	0.010*
	(0.008)	(0.005)	(0.007)	(0.005)
Inverse Mills ratio	−0.108***	0.055***		
	(0.009)	(0.005)		
Observations	30,372,267	12,801,617	30,372,267	12,801,617
Estimation method	OLS	OLS	OLS	OLS

Notes: The table reports the effects of the business cycle on training participation of the employed and the not employed. Estimates in Columns (1) and (2) include the inverse Mills ratio, while estimates in Columns (3) and (4) do not. Each regression also includes age, gender, a dummy for tertiary education, year and country dummies, and country-specific employment trends. Standard errors clustered by country and time period are reported in parentheses. OLS, ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

than in Column (2). One reason why this happens is that, when unemployment increases, some individuals moving from employment to unemployment engage in retraining activities, often funded by active labor market policies.

Next, we also ask whether the results discussed herein are homogeneous across worker characteristics (gender, schooling, and age) and industries (only for the employed). Our results are reported in Table 6. We find that training is more countercyclical for females than for males, both for the employed and the not employed. Countercyclical effects are stronger in public and private services than in manufacturing and are more pronounced among the better educated, in line with the view that liquidity constraints, which are more likely to be present among the less educated, can hamper participation in a recession.

5.2 The effects of the business cycle on training intensity

Training participation does not account for the variations in the intensity of training, conditional on participation. In this subsection, we consider the effects of the business cycle on training hours during the previous 4 weeks and assign 0 hours to individuals who report that they have not participated in training during the same period.

Results for the full sample and for the subsamples of employed and not employed individuals are reported in Table 7. We find that the effect of the business cycle on training hours is negative but not statistically significant in the full sample (−0.004, standard error: 0.013), positive but imprecisely estimated in the subsample of the employed (0.001, standard error: 0.011), and negative and statistically significant in the subsample of the not employed (−0.078, standard error: 0.023). Therefore, although training for the not employed does not vary in a significant way with the business cycle along the extensive margin (participation), its intensity increases in an expansion and declines in a recession. In particular, we estimate that a 1%

Table 6 The effects of the business cycle (*U_cycle*) on training participation (by gender, age, education and industry)

	(1)	(2)	(3)
Cyclical component of unemployment rate × 10	**All**	**Employed**	**Not Employed**
Males	0.011*	0.011*	−0.002
	(0.006)	(0.006)	0.006
Females	0.018**	0.030***	0.011**
	(0.007)	(0.009)	(0.006)
Age 25–44 years	0.015**	0.026***	0.015***
	(0.007)	(0.008)	(0.005)
Age 45–64 years	0.015**	0.038***	0.015**
	(0.006)	(0.007)	(0.005)
Less-than-upper-secondary education	0.002	0.022***	−0.007
	(0.006)	(0.008)	(0.006)
Upper secondary education	0.011**	0.009	0.005
	(0.005)	(0.005)	(0.005)
Tertiary education	0.039***	0.042***	0.034***
	(0.001)	(0.015)	(0.012)
Manufacturing		0.011	
		(0.008)	
Private services		0.023**	
		(0.009)	
Public services		0.039**	
		(0.015)	

Notes: The table reports the effects of the business cycle on training participation. The dependent variable is listed in the heading of each column. Estimates refer to the full sample in Column (1), to the employed in Column (2), and to the not employed in Column (3). Each regression also includes year and country dummies, country-specific employment trends and, when appropriate, age, gender, a dummy for tertiary education. Columns (2) and (3) include also the estimated inverse Mills ratio. Standard errors clustered by country and time period are reported in parentheses.

**p*<0.1; ***p*<0.05; ****p*<0.01.

increase in the unemployment rate reduces hours of training for the not employed by 6.67% with respect to the sample mean (0.078/1.170).

5.3 Training, the business cycle, and labor market institutions

The relationship between training and the business cycle may depend on labor market institutions. For instance, labor market policies that encourage training during recessions typically include measures that promote training of the unemployed. We measure the generosity of these policies by using the share of public expenditure for training as share of the gross domestic product (GDP) (source: OECD). We consider the data for 2004, the year before our sample period begins, to avoid endogeneity concerns. This share is the highest in Denmark (0.52%) and Germany (0.44%) and is the lowest in Slovakia (0.01%) and the Czech Republic (0.02%).

Table 7 The effects of the business cycle (*U_cycle*) on training hours and employment status

	(1)	(2)	(3)	(4)
Dependent variable	**Training hours**	**Employment probability**	**Training hours**	**Training hours**
Sample	**All**	**All**	**Employed**	**Not Employed**
Cyclical component of unemployment rate × 10	−0.038	−0.004***	0.006	−0.783***
	(0.133)	(0.001)	(0.011)	(0.022)z
Demand shock: Z_{ct}		0.007***		
		(0.001)		
Inverse Mills ratio			0.099	7.073***
			(0.147)	(0.386)
Male	−0.116***	0.140***	−0.130***	1.916***
	(0.011)	(0.002)	(0.039)	(0.095)
Age	−0.034***	−0.008***	−0.025***	−0.159***
	(0.001)	(0.001)	(0.002)	(0.007)
Has tertiary education	1.044***	0.154***	0.970***	3.341***
	(0.032)	(0.002)	(0.037)	(0.142)
R-squared	0.018	0.098	0.019	0.028
Observations	43,173,984	43,173,984	30,372,267	12,801,617
Estimation method	OLS	Probit	OLS	OLS

Notes: The table reports the effects of the business cycle on employment and training hours. The dependent variable is listed in the heading of each column. Estimates refer to the full sample in Columns (1) and (2), to the employed in Column (3), and to the not employed in Column (4). Column (2) reports the marginal effects using a probit specification. Each regression also includes year and country dummies and country-specific employment trends. For the probit specification, the pseudo-*R*-squared value is reported instead of the *R*-squared value. Standard errors clustered by country and time period are reported in parentheses. OLS, ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

The sensitivity of training to the business cycle could depend also on labor market flexibility, which we capture using the OECD index of employment protection for 2004. We expect that the higher the protection, the more difficult it is to dismiss employees and the higher the incentive to train them. In 2004, protection was the highest in Italy, Latvia, and the Netherlands and the lowest in Ireland, Finland, and Denmark.

We estimate the relationship among employment protection, public training expenditure, and the sensitivity of training participation to the business cycle using a two-step approach (see Betts, 1995). In the first step, we estimate Eq. (1) for training participation by country and retrieve both the estimated coefficient and the standard error associated with cyclical unemployment. In the second step, we regress these coefficients on a constant term, the share of public training expenditure, and the degree of employment protection, using the reciprocal of the variance of the first-stage estimates as the weight.[9] The results in Table 8 show that the

9 By doing so, we give more importance to precisely estimated coefficients.

Table 8 The relationship among employment protection, public training expenditure on GDP, and the sensitivity of training participation to the business cycle: second step estimate

Dependent variable: the sensitivity of training participation to the business cycle	
Employment protection index	0.022**
	(0.010)
Public expenditure for training as % of GDP	0.045*
	(0.023)
Observations	22
R-squared	0.25

Notes: Robust standard errors. The regression is weighted using the reciprocal of the variance of first-stage coefficients. GDP: gross domestic product.

*p<0.1; **p<0.05; ***p<0.01.

sensitivity of training to cyclical unemployment is higher in countries with higher employment protection and a higher share of public training expenditure, as expected.

6 Conclusions

We have investigated the cyclicality of training in Europe, using data from the EU-LFS for the period 2005–2018. Pooling data across all EU-27 countries, as well as across employed and not employed workers, we have estimated that training participation is mildly countercyclical, while training intensity is acyclical.

Considering that firm-sponsored training is mostly undertaken by employed workers and that firms are likely to encourage training during recessions, these average effects may hide heterogeneities by employment status. As a result, we have estimated the response of training to the business cycle separately for employed and not employed workers. We have found that training participation (intensity) is countercyclical (acyclical) for the employed and acyclical (procyclical) for the not employed. Countercyclical training of the employed is consistent with the view of recessions as times of reorganization. Procyclical learning for the not employed is driven instead by the behavior of the inactive and can be explained by the presence of credit constraints preventing investment when the economy is in dire straits.

What are the implications of countercyclical training for the European economy? The available evidence suggests that labor productivity typically increases in economic expansions and declines in economic downturns. If training does not subtract workers' time from production during recessions, when labor demand is low, and positively affect labor productivity, countercyclical skill accumulation can contribute to attenuation of the procyclical behavior of productivity, in the sense that the slowdown in productivity would have been sharper in the absence of training.

We have shown that in the countries of Europe where training increases during recessions, governments spend more to encourage training and have a higher share of training expenditure on GDP. Government expenditure includes cofinancing schemes directed at firms (levy/grant programs and tax credits) and at individuals (vouchers, individual learning accounts). Although these schemes may induce deadweight losses (by funding training that would have been done anyway), they can increase adult learning by reducing the liquidity constraints faced by workers and firms, especially during recessions (see Costa et al., 2018).

Training investment during recessions can be stimulated by designing countercyclical subsidies, which increase in intensity when the economy is in a recession and the likelihood that liquidity constraint bite is higher. Examples in this direction are the topups to individual learning accounts introduced by France and Singapore to promote training during the coronavirus disease (COVID) recession.

We have also shown that training participation increases more with cyclical unemployment in countries where employment protection is stronger. In these countries, the dismissal of employees when the economy slows down is either costlier or more complicated, which favors training of redundant labor as an alternative viable option. An implication of this is that policies favoring the deregulation of labor markets may have the unpleasant side effect of reducing the incentives that firms have to train labor during recessions.

Declarations

Availability of data and material

Access to the data was granted by Eurostat (research project 199/2020). The original data cannot be obtained from the authors and require a successfull application to Eurostat.

Results and conclusions are ours and not those of Eurostat, the European Commission, or any of the national authorities whose data have been used.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors contributed equally.

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References

Alessandrini, D.; S. Kosempel; T. Stengos (2015): The Business Cycle Human Capital Accumulation Nexus and its Effect on Hours Worked Volatility. Journal of Economic Dynamics and Control 51, 356-377.

Autor, D.; D. Dorn; G. Hanson (2013): The China Syndrome: Local Labour Market Effects of Import Competition in the United States. American Economic Review 103(6), 2121-2168.

Bassanini, A.; A. Booth; G. Brunello; M. De Paola; E. Leuven (2007): Workplace Training in Europe, in: Brunello, G.; P. Garibaldi; E. Wasmer (eds.), Education and Training in Europe, Oxford, United Kingdom, Oxford University Press.

Bassanini, A.; G. Brunello (2008): Is Training More Frequent When the Wage Premium is Smaller? Evidence from the European Community Household Panel. Labour Economics 15(2), 272-290.

Betts, J. (1995): Does School Quality Matter? Evidence from the National Longitudinal Survey of Youth. Review of Economics and Statistics 77(2), 231-247.

Brunello, G. (2009): The Effect of Economic Downturns on Apprenticeships and Initial Workplace Training: A Review of the Evidence. Empirical Research in Vocational Education and Training 1(2), 145-171.

Brunello, G.; M. Bertoni (2021): Human Capital During Recessions, EENEE Analytical Report NO.43. Brussels, The European Commission.

Costa, R.; N. Datta; S. Machin; S. McNally (2018): Investing in People: The Case for Human Capital Tax Credits, London, United Kingdom, CEP LSE.

Felstead, A.; F. Green (1996): Training Implications of Regulation Compliance and Business Cycles, in: Booth, A.L.; D.J. Snower(eds.), Acquiring Skills: Market Failures, Their Symptoms and Policy Responses. New York, Cambridge University Press, 255-284.

Felstead, A.; F. Green; N. Jewson (2012): An analysis of the impact of the 2008-09 recession on the provision of training in the UK, Work, Employment and Society 26(6), 968-986.

Hall, R. E. (1991): Recessions as reorganizations. NBER macroeconomics annual, 17-47.

Hodrick, R.; E. Prescott (1997): Postwar US Business Cycles: An Empirical Investigation. Journal of Money Credit and Banking 29(1), 1-16.

Lüthi, S.; S.C. Wolter (2020): Are Apprenticeships Business Cycle Proof? Swiss Journal of Economics and Statistics 156(1), 3.

Majumdar, S. (2007): Market Conditions and Worker Training: How Does it Affect and Whom? Labour Economics 14, 1-23.

Méndez, F.; F. Sepúlveda (2012): The Cyclicality of Skill Acquisition: Evidence from Panel Data. American Economic Journal: Macroeconomics 4(3), 128-152.

Muehlemann, S; H. Pfeifer; B.H. Wittek (2020): The Effect of Business Cycle Expectations on the German Apprenticeship Market: Estimating the Impact of COVID-19. Empirical Research in Vocational Education and Training 12(1), 1-30.

OECD (2001): Labor Market Policies that Work. Paris, OECD.

Ravn, M.O.; H. Uhlig (2002): On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. Review of Economics and Statistics 84(2), 371-376.

Sepulveda, F. (2004): Training and Business Cycles. *Available at SSRN 830404.*

Appendix

Table A1 The effects of the business cycle (*U_cycle*) on training participation by employment status – 5% random sample by country and time period

	(1)	(2)
Dependent variable	**Training participation**	**Training participation**
Sample	**Employed**	**Not employed**
Cyclical component of unemployment rate × 10	0.021***	0.007
	(0.008)	(0.007)
Inverse Mills ratio	−0.110***	0.045***
	(0.012)	(0.012)
Observations	1,518,752	639,964

Notes: Bootstrapped standard errors. The table reports the effects of the business cycle on training participation in a 5% random sample by country and time period. Column (1) is for the employed, and Column (2) represents the unemployed. Each regression also includes age, gender, a dummy for tertiary education, year and country dummies, and country-specific employment trends. Standard errors reported in parentheses are obtained from 200 bootstrap replications (clustered by country and time period). In each replication, we estimate the probit specification for selection into employment, the inverse Mills ratio, and the effect of *U_cycle* on training for the employed and the not employed (OLS regressions). OLS, ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

Table A2 The effects of the business cycle (*U_cycle*) on training participation and labor force participation status

	(1)	(2)	(3)	(4)
Dependent variable	**Training participation**	**Labor force participation**	**Training participation**	**Training participation**
Sample	**All**	**All**	**Active**	**Inactive**
Cyclical component of unemployment rate × 10	0.015**	−0.006**	0.019**	0.005
	(0.006)	(0.003)	(0.007)	(0.005)
Demand shock: Z_{ct}		0.004***		
		(0.001)		
Inverse Mills ratio			−0.062***	0.086***
			(0.005)	(0.035)
Male	−0.015***	0.145***	−0.035***	0.015***
	(0.001)	(0.002)	(0.002)	(0.001)
Age	−0.001***	−0.010***	0.001***	−0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
Has tertiary education	0.058***	0.126***	0.048***	0.052***
	(0.002)	(0.001)	(0.002)	(0.002)
R-squared	0.076	0.098	0.077	0.062
Observations	43,173,984	43,173,984	30,372,267	12,801,617
Estimation method	OLS	Probit	OLS	OLS

Notes: The table reports the effects of the business cycle on employment and training participation. The dependent variable is listed in the heading of each column. Estimates refer to the full sample in Columns (1) and (2), to active workers (employed plus unemployed) in Column (3), and to the inactive in Column (4). Column (2) reports the marginal effects from a probit specification. Each regression also includes year and country dummies and country-specific employment trends. For the probit specification, the pseudo-R-squared is reported instead of the R-squared value. Standard errors clustered by country and time period are reported in parentheses.

OLS, ordinary least squares.

*$p<0.1$; **$p<0.05$; ***$p<0.01$.